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UNCERTAINTIES IN LCA

Erratum to: A global approach for sparse representation of uncertainty in Life Cycle Assessments of waste management systems

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A GLOBAL APPROACH FOR SPARSE REPRESENTATION OF UNCERTAINTY IN LIFE CYCLE ASSESSMENTS OF WASTE MANAGEMENT SYSTEMS

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Abstract

Purpose Identification of key inputs and their effect on results from Life Cycle Assessment (LCA) models is fundamental. Because parameter importance varies greatly between cases due to the interaction of sensitivity and uncertainty, these features should never be defined *a priori*. However, exhaustive parametrical uncertainty analyses may potentially be complicated and demanding, both with analytical and sampling methods. Therefore, we propose a systematic method for selection of critical parameters based on a simplified analytical formulation that unifies the concepts of sensitivity and uncertainty in a Global Sensitivity Analysis (GSA) framework.

Methods The proposed analytical method based on the calculation of Sensitivity Coefficients (SC) is evaluated against Monte Carlo sampling on traditional uncertainty assessment procedures, both for individual parameters and for full parameter sets. Three full-scale waste management scenarios are modelled with the dedicated waste LCA model EASETECH and a full range of ILCD recommended impact categories. Common uncertainty ranges of 10 % are used for all parameters, which we assume to be normally distributed. The applicability of the concepts of additivity of variances and GSA is tested on results from both uncertainty propagation methods. Then, we examine the differences in discernibility analyses results carried out with varying numbers of sampling points and parameters.

Results and discussion The proposed analytical method complies with the Monte Carlo results for all scenarios and impact categories but offers substantially simpler mathematical formulation and shorter computation times. The coefficients of variation obtained with the analytical method and Monte Carlo differ only by 1 %, indicating that the analytical method provides a reliable representation of uncertainties and allows determination of whether a discernibility analysis is required. The additivity of variances and the GSA approach show that the uncertainty in results is determined by a limited set of important parameters. The results of the discernibility analysis based on these critical parameters vary only by 1 % from discernibility analyses based on the full set but require significantly fewer Monte Carlo runs.

Conclusions The proposed method and GSA framework provide a fast and valuable approximation for uncertainty quantification. Uncertainty can be represented sparsely by contextually identifying important parameters in a systematic manner. The proposed method integrates with existing step-wise approaches for uncertainty analysis by introducing a global importance analysis before uncertainty propagation.

Keywords: LCA, Uncertainty propagation, Analytical methods, Monte Carlo, Global Sensitivity Analysis, Total variance

1 Introduction

Uncertainty analysis is essential for a balanced interpretation and use of Life Cycle Assessment (LCA) in decision-making. In relation to waste, LCA is gaining increased use for quantification of the environmental performance and sustainability of alternative management solutions (Laurent et al. 2014a; Laurent et al. 2014b). LCAs of waste management systems are often relatively complex models, where the results are subject to uncertainty due to combined effects of inherent data variability, unrepresentative datasets, and modelling assumptions (Clavreul et al. 2012). In order to ensure transparency and reliability of modelling of such systems, identification of the most important factors and understanding of the mechanisms by which they influence the results are fundamental.

Several authors have investigated uncertainty in LCA and agree on categorizing the relevant factors as parameter, scenario, and model uncertainties (Heijungs et al. 2005; Lloyd and Ries 2007; Clavreul et al. 2012). As far as parameters are concerned, critical data inputs in waste LCAs are commonly: chemical waste composition, material and energy recovery efficiencies, etc.

However, the relevance of these factors cannot be defined *a priori*. Rather, the importance of a parameter is a global concept, defined by the interaction of the parameter´s sensitivity and uncertainty (Heijungs, 1996). While the sensitivity accounts for the weight of a parameter in the case-specific model configuration, the uncertainty related to a parameter does not depend on the system, but on the parameter´s nature and characteristics. For these reasons, critical factors should be identified with a systematic and rigorous approach that integrates sensitivity and uncertainty on a case-by-case basis, such as life-cycle screening (Heijungs, 1996).

In LCAs of waste management systems, the approach previously suggested in the literature was instead a sequence of contributions, sensitivity and uncertainty analyses (e.g. Clavreul et al., 2012; Heijungs and Kleijn, 2001, Laurent et al., 2014b). For uncertainty analysis, different approaches are available: propagation by analytical or sampling based methods. The analytical approaches are based on the theory of error propagation (Ciroth et al. 2004) and address with differential calculus how input uncertainties propagate into the output uncertainties through the LCA mathematical model (Groen et al. 2014). Multiple analytical expressions based on a wide range of formulations and assumptions are present in the literature (Heijungs et al. 2005; Heijungs 2010; Hong et al. 2010; Clavreul et al. 2012; Imbeault-Tétreault et al. 2013). Alternatively, sampling methods consist of repeatedly calculating the impact scores with inputs randomly sampled from specified probability distributions (Imbeault-Tétreault et al. 2013). Most LCA software tools facilitate uncertainty propagation by means of sampling methods, mostly based on Monte Carlo simulations (Lloyd and Ries 2007).

These two classes of error propagation approaches have been compared by a number of authors with respect to data input needs, formulas, and types of output, in the light of their foundation and implementation in LCA and emphasizing performance-wise differences and similarities. Quantitative comparisons in literature demonstrate that the two methods provide similar results but differ with respect to output type, input data requirements and computing time (Heijungs and Lenzen 2014; Groen et al. 2014). Overall, analytical methods require shorter computing times and facilitate extraction of preliminary uncertainty information when large numbers of input parameters are considered and the input uncertainties are small (Groen et al. 2014). On the other hand, sampling methods produce a sample of results from which several statistics can be computed and provide more types of information (Heijungs and Lenzen 2014). Various drawbacks of these approaches have been emphasized in literature: from analytical methods, the output of a single variance value does not allow visualization of the uncertainty as a probability distribution, nor the performance of discernibility analyses (Heijungs and Lenzen 2014). In particular, the analytical formulation involving Taylor series expansion (Heijungs et al. 2005; Heijungs 2010) was found to be impractical in case of the large and complex scenarios often applied in waste LCAs (Clavreul et al. 2012). Nonetheless, sampling methods involving Monte Carlo techniques are computationally intensive and do not automatically assess the sensitivity and contribution of individual parameters to the total parametrical uncertainty (Hong et al. 2010; Heijungs and Lenzen 2014). Finally, the accuracy of sampling methods is often hampered by the difficulty of assigning the required uncertainty distributions to the often numerous parameters in an LCA model (Hong et al. 2010).

Therefore, the task of identifying critical factors of a waste management LCA on a case-by-case basis becomes highly complicated when all the aspects of these models have to be included for the uncertainty propagation, especially in real-scale case studies and across multiple impact categories. Following the tiered approaches of Heijungs et al. (2005) and Clavreul et al. (2012), sensitivity and uncertainty analyses are most often done separately, where uncertainty propagation is rarely carried out due to its perceived complexity (Laurent et al., 2014b). However, *a priori* and unjustified exclusion of individual parameters does not offer a valid approach to uncertainty propagation. Indeed, the full influence of input parameters with a low sensitivity and a high uncertainty would not be quantified, especially in cases where the uncertainty is propagated only for highly sensitive parameters, e.g. Clavreul et al. (2012), leading to iterative revisions of the model results (Saltelli et al., 2006). A systematic "importance measure" approach that includes analysis of the fundamental connections between sensitivity and uncertainty of individual parameters, commonly known also as Global Sensitivity Analysis (GSA), has been identified as the best practice, *inter alia*, by Saltelli et al. (2006), but has never been applied explicitly by existing literature on waste management LCAs.

GSA aims to ascertain how a specific system depends on the model structure and the information entered into the model. GSA offers a thorough assessment framework that can provide guidance for improving reliability, transparency and credibility of environmental assessments (Kioutsioukis et al. 2004). GSA methods subdivide into variance-based and moment-independent importance measures. The first exploit the law of total variance, or Sobol's functional variance decomposition (Sobol' 2001), and are characterized by identifying the most important variables in a global perspective, thus allowing to focus on improving the quality of critical input data. Similar approaches in LCA literature appear with different names, e.g. "life-cycle screening" (Heijungs et al., 1996), "key issue analysis" (Heijungs et al., 2005), "uncertainty contribution analysis" (Clavreul et al., 2012), and "contribution to variance" (Heijungs and Lenzen, 2014). Moment-independent methods calculate the difference in the uncertainty in output that would be provided by knowing the value of parameters in input, one at a time. However, the separation between unconditional and conditional output densities becomes smaller with a high number of parameters in the model and implementation of this technique might be problematic for models with long computational times (Borgonovo et al., 2011). Variance-based importance measures thus seem to be more suitable for vast models with countless parameters such as waste-LCAs. So far, very little attention has been devoted to the possibility of explaining a large proportion of the variability in environmental impacts with a limited number of parameters (Bala et al. 2010). Only a few studies have proposed a systematic method for identification of the most influential parameters in LCA: Padey et al. (2012) presented a method where a general variance decomposition based on the Sobol' indices was applied to quantify the influence of input parameters on result variability. Meinrenken et al. (2012, 2014) applied parameter screening for a concurrent uncertainty contribution analysis during the data gathering phase. While any cut-off threshold for selection of critical parameters should be based on multiple impact categories rather than a single impact category, existing literature on uncertainty in LCA has focused primarily on climate change impacts (Bourgault et al., 2012). Consistent assessment of uncertainties in the increasingly complex scenarios assessed in state-of-the-art waste LCAs (e.g. a wide range of waste material fractions, treatment, recovery and disposal technologies) requires a more systematic approach to identify critical factors and quantify their contribution to uncertainty.

The objective of this paper is to provide a systematic and reproducible method for identification and uncertainty propagation of important parameters in a GSA perspective for application in waste LCA modelling, based on and aiming to simplify and improve existing tiered approaches. Three full-scale waste management alternatives for municipal solid waste in Denmark were modelled with the dedicated waste LCA model EASETECH (Clavreul et al. 2014). A sensitivity analysis was carried out according to the sequential approach described in Clavreul et al. (2012); then, uncertainties were propagated (i) analytically and (ii) by means of Monte Carlo sampling. A discernibility analysis was carried out comparing scenarios modelled based on uncertainty propagation of the full set of parameters and scenarios modelled with uncertainty propagation only of the parameters identified as critical in a GSA perspective. The analysis was performed with normal probability distributions for parameters and for all ILCD recommended impact categories.

2 Methods

2.1 Sensitivity analysis

Sensitivity analysis constitutes a well-established phase in traditional uncertainty quantification approaches, and is the first step in applying GSA to an LCA scenario. Sensitivity analysis identifies how results vary as a consequence of a change in the model input values and is composed by: contribution analysis (results decomposition into processes and substances), perturbation analysis and calculation of sensitivity coefficients. In the perturbation analysis each parameter is increased by a limited numerical amount in a "one-at-a-time" (OAT) manner while keeping all other parameters fixed at their nominal value. For an increment of the value of the input parameter *i*, a new impact score is calculated and compared with the initial score within the same impact category *j*. The following ratios are calculated:

The sensitivity coefficient (SC), which is the ratio between two absolute changes:

$$SC_i^j = \frac{(\Delta\ \mathrm{result})^j}{(\Delta\ \mathrm{parameter})_i} \approx \frac{\partial z_j}{\partial x_i} \tag{1}$$

The sensitivity ratio (SR), which is the ratio between the two relative changes:

$$SR_i^j = \frac{\left(\frac{\Delta \text{ result}}{\text{initial result}}\right)^j}{\left(\frac{\Delta \text{ parameter}}{\text{initial parameter}}\right)_i} \approx \frac{\partial z_j}{\partial x_i}\frac{x_i}{z_j} \quad (2)$$

With i=1,…,n tested parameters in the model and j=1,…,m impact categories in the characterization method selected for the calculation of the impacts. The second expression complies with Heijungs and Lenzen (2014), where $z=z(x,y)$ is the model result, x_i the input parameter and j the impact category.

2.2 Uncertainty propagation

Parametrical input uncertainties are systematically propagated into output uncertainties with analytical or sampling methods, as previously explained. At this stage, the LCA practitioner chooses whether to represent uncertainty according to the probability or possibility theory. The first assumes that all uncertainties can be represented by single probability distributions, thus referring to stochastic uncertainty related to measured data variability and fluctuations. Here the probability theory is applied as the focus was placed on the uncertainty propagation theory rather than the nature of the data. Laurent et al. (2014b) highlighted how it is a common difficulty to represent the uncertainties of the input data that will be propagated in the model: please refer to the Supporting Information for further instructions on how to provide input uncertainty.

2.2.1 Analytical uncertainty propagation

Analytical uncertainty propagation in LCA has been addressed by a number of authors, with various formulations and assumptions. As explained, *inter alia*, by Ciroth et al. (2004), the analytical approach is based on the theory of error propagation, where the influence of perturbations can be approximated by differential calculus. Using the first order approximation of the Taylor series, the uncertainty associated with the function $z=z(x,y)$, is:

$$V(z) \approx \left(\frac{\partial z}{\partial x}\right)^2 \cdot V(x) + \left(\frac{\partial z}{\partial y}\right)^2 \cdot V(y) + 2\frac{\partial z}{\partial x}\cdot\frac{\partial z}{\partial y}\cdot COV(x,y) \quad (3)$$

The uncertainty is thus given by the partial first-order derivatives of the function, multiplied by the input uncertainty associated with the parameters, $V(x)$ and $V(y)$. In Eq. (3), the covariance term includes the possibility that the errors of the variables x and y are correlated (Heijungs and Lenzen 2014).

The correlation structure among variables in LCA is rarely investigated (Bojacá and Schrevens 2010), as in most cases the covariance is assumed to be negligible and uncertainties to be independent (Heijungs et al. 2005). In such cases, the covariance can be set to zero and Eq. (3) simplified to:

$$V(z) \approx \left(\frac{\partial z}{\partial x}\right)^2 \cdot V(x) + \left(\frac{\partial z}{\partial y}\right)^2 \cdot V(y) \quad (4)$$

Where *V(x)* and *V(y)* can be associated with any type of underlying distribution. Examples of the values the first order derivative may assume can be found in Heijungs (2010), Hong et al. (2010, 2012) and Imbeault-Tétreault et al. (2013). Eq. (4) can be further approximated according to Heijungs et al. (2005) and the SC method introduced by Clavreul et al. (2012). A small change, Δx of an input parameter x, leads to a change Δz in the result z, as explained in Section 2.1. This leads to the approximation of the first-order derivative with the relative change, and thus SC as in (1).

$$\frac{\partial z_j}{\partial x_i} \approx \frac{\Delta z_j}{\Delta x_i} = SC_x^j \tag{5}$$

The SC method was tested against the Taylor series expansion method by Clavreul et al. (2012). The results varied by less than 0.5 %, confirming that the simpler SC method can be used as a good approximation.

The analytical approach for error propagation presented in this paper is based on the abovementioned findings in literature and the following assumptions:

i) The model is linear. In reality, an LCA model is composed of mixed equations of multiplications and sums of variables, calling into question the validity of the first order approximation. However, as shown by Imbeault-Tétreault et al. (2013), the difference between the results obtained with sampling methods did not justify the use of a more complex analytical method. ii) Independence between model input parameters (univariate distributions). As a first approximation, including covariance for all input parameters was recognized as an unfeasible task also by Huijbregts et al. (2003). iii) An unspecified form of the probability distribution of input parameters. Contrary to Hong et al. (2010, 2012) and Imbeault-Tétreault et al. (2013), Heijungs et al. (2005, 2010 and 2014) highlight that it suffices to specify the first two moments of the distribution (mean and variance). The same approach was followed by Groen et al. (2014).

Schematizing a general LCA with a mathematical relationship as:

$$Y^j = f(X_1, \ldots, X_n) \tag{6}$$

Where Y is the result score for the impact category j, depending on an n number of input parameters X_i. Then the analytical uncertainty for the individual parameter, i, is given by:

$$V(Y)_i^j \approx \left(SC_i^j\right)^2 \cdot V_{input}(X_i) \tag{7}$$

Where V_{input} is the initial uncertainty associated to the i-th parameter X_i.

When considering all parameters in a scenario, the total parametrical variance corresponds to:

$$V(Y)^j \approx \sum_{i=1}^{n} \left[\left(SC_i^j\right)^2 \cdot V_{input}(X_i)\right] \tag{8}$$

The variance in the result score in a specific impact category, j, will thus be given by the sum of the single parameter uncertainties. These are determined by a fixed initial input uncertainty and the specific SC of the i-th parameter in that impact category.

2.2.2 Uncertainty propagation with Monte Carlo sampling

Selected input parameters are represented by a stochastic variable with a defined probability distribution. The Monte Carlo analysis randomly samples a value within each uncertainty distribution and calculates the LCA impact scores. This is repeated for $k=1,\ldots,N$ number of runs providing k set of results. These LCA result scores can then be evaluated by the associated statistical properties, such as expected value and variance, or by constructing a frequency histogram and computing a probability distribution representing the model results. Independence between model parameters is assumed, as for the analytical uncertainty propagation.

2.3 Discernibility analysis

In an LCA context, discernibility analysis aims at unifying comparative and uncertainty analyses. The comparison between results expressed as probability distributions was addressed by many authors (Huijbregts 1998; Heijungs and Klein 2001; Heijungs et al. 2005; Hong et al. 2010; Clavreul et al. 2012; Imbeault-Tétreault et al. 2013; Heijungs and Lenzen 2014). Hong et al. (2010) underlined how the uncertainty of the difference between scenarios might depend on shared parameters, due to the many processes and characterization factors common between scenarios. According to Clavreul et al. (2012), this can be relevant because some uncertainties may have the same influence on the scenarios and, therefore, no influence on the ranking. The discernibility analysis functions as a *pair-by-pair* evaluation of the difference (Heijungs and Klein 2001; Heijungs et al. 2005; Clavreul et al. 2012) or the ratio (Huijbregts 1998) between scenarios. Results of the discernibility analysis might be easier to communicate by presenting only the percentage of cases where one scenario obtains more favourable results than another, especially if there are more than two scenarios (Heijungs and Kleijn 2001; Heijungs et al. 2005; Clavreul et al. 2012).

2.4 Law of total variance

GSA variance-based techniques estimate the fractional contribution of each input variable X_i to the variance of Y (Archer et al. 1997). Eq. (4) shows that in the case of independent model parameters, the total uncertainty can be approximated by the sum of the single parametrical uncertainties. The more general case is defined by Sobol's ANOVA-representation (Sobol′ 2001). With a model of the form $Y=f(X_1, X_2, \ldots, X_n)$, the total variance of the model output, $V(Y)$, is decomposed as:

$$V(Y) \approx \sum_{i=1}^{n} V_i + \sum_{i=1}^{n} \sum_{i<z} V_{iz} + \ldots + V_{1,2,\ldots n} \tag{9}$$

Where i denotes the number of parameters in the model (n), and z the subset of second order interacting parameters. Taking the first order approximation, the so-called "contribution to variance" is the ratio between first order effects (V_i) and the overall variance, also known as Sobol's sensitivity indexes, S_i (Saltelli et al. 2010). The V_i obtained with the first order approximation (Eq. (11)) corresponds to the terms added in Eq. (4), to the single-parameter analytical uncertainty in Eq.(7) and to the contribution to variance (CTV) mentioned in Heijungs and Lenzen (2014).

$$S_i = \frac{V_i}{V(Y)} \tag{10}$$

Where

$$V_i = V(Y)_i^j \approx \left(\frac{\partial z_i}{\partial x_i}\right)^2 \cdot V(x) \approx \left(SC_i^j\right)^2 \cdot V_{input}(X_i) = CTV(Y^j, x_i) \tag{11}$$

The estimation of S_i indexes allows ranking the input variables according to their importance for the model result (Sobol′ 2001). In the case of an LCA with *j* impact categories, the single variance contributions can be formulated according to Eq. (7) and the total variance according to Eq. (8). Then, this contribution can be decomposed as:

$$V(Y)^j \approx \sum_{i=1}^{n} V_i^j \approx \sum_{i=1}^{r} V_i^j + \sum_{i=r+1}^{n} V_i^j \tag{12}$$

Where *r* represents the number of parameters which, summed progressively according to their importance in the model, is required to reach a desired representativeness level of the total parametrical uncertainty in a scenario. Ranking the most important parameters allows prioritization of efforts to improve data quality in a systematic and consistent way. This concept thereby unifies sensitivity and uncertainty related to input parameters into importance in a GSA framework.

3 Case study

3.1 Case study scenarios and impact categories

A hypothetical case study was defined in order to evaluate the combined sensitivity and uncertainty analysis described in the previous sections. The emphasis was placed on the methodological aspects and application of the analysis method rather than on intense data collection; however, the scenarios have been defined to reflect features of full-scale waste management systems in a Danish context. The case study includes three scenarios for management of single family household waste in Denmark in 2013 (Jensen et al. 2013). The scenarios are based mainly on the following technology combinations: S1) Recycling + incineration, S2) Recycling + incineration + anaerobic digestion, and S3) Recycling + landfilling.

The technology processes included in the model were obtained from the EASETECH model database (Clavreul et al. 2014). The study presents results for climate change (GWP), stratospheric ozone depletion (ODP), human toxicity, cancer (HTc) and non-cancer (HTnc) effects, particulate matter (PM), ionizing radiation (IR), photochemical ozone formation (POFP), terrestrial acidification (TA), terrestrial eutrophication (TE), freshwater eutrophication (FE), marine eutrophication (ME), freshwater ecotoxicity (ET), fossil resources depletion (RDfos), metals/minerals depletion (RD). All characterization methods and normalization references are selected among those recommended by European Commission (2010). The case study does not aim to evaluate the latest impact categories, but rather to illustrate the validity of the methodology applied. The time horizon of the study was 100 years. The case study simulates a decision support LCA that involves consequences that result in additionally installed or additionally decommissioned equipment/capacity outside the foreground system of the analysed system. Consequently, the decision context falls within Situation B (meso/macro level decision support for technology scenarios) according to European Commission (2010). The LCI was modelled following a consequential approach and multi-functionality in the model was addressed by substitution. Please refer to the Supporting Information for details on the modelled framework and technologies.

3.2 EASETECH model

All three scenarios were modelled with EASETECH (Clavreul et al. 2014), an LCA model facilitating advanced LCA of waste management systems. The model enables modelling of a reference flow consisting of a mix of material fractions and tracking of substances within the individual material fraction flows, from generation to final release of substances to the environment. The model is particularly well suited for the focus of this paper, since EASETECH allows the use of parameters in all input fields. For each parameter the user can specify one value, a list of values or a probability distribution (normal, uniform, log-normal or triangular). The uncertainty of the obtained LCA results can be propagated with a Monte Carlo simulation tool.

3.3 Case study evaluation approach

The case study was evaluated following the set-up of established tiered approaches involving: (a) sensitivity analysis, (b) uncertainty propagation with Monte Carlo analysis, (c) discernibility analysis. However, the SCs were used to propagate the uncertainty also analytically, and results of the two propagation methods were compared. The concepts of additivity of variances and GSA were applied before the discernibility analysis *(v)* in order to evaluate the insights gained from the parameter screening against the discernibility results of the traditional approach. For illustration and simplicity, the input variance associated to the parameters follows a predefined common uncertainty range of 10 % for all parameters, which are assumed to be normally distributed and with a 95 % confidence interval. Please refer to the Supporting Information for comparisons carried out with other uncertainty ranges and distribution types.

(a) For each scenario and impact category, normalized impact scores were calculated and used for contribution analysis, which allowed identification and parameterization of relevant LCA model inputs. These parameters were then employed for an OAT perturbation analysis. SCs and SRs were calculated with Eq. (1) and (2) for all parameters in the three scenarios for equal parameter variations of +10 %.

(b) The uncertainty propagation was carried out, first for individual parameters and then for the entire set of parameters, for all impact categories and all three scenarios. Then, results obtained analytically (Eq. (7) and (8)) and by means of the Monte Carlo simulations were compared. The Monte Carlo simulation was carried out with increasing number of sampling points (N=1000, 10000, 100000). For each N, the differences from the analytical result were calculated as a percentage. When comparing the variance associated with the entire sets of parameters, the coefficient of variation (CV) was also determined:

$$CV^{j} = \frac{\sqrt{V(Y)^{j}}}{Y^{j}} \tag{13}$$

The CV is specific for each impact category *j* and is expressed as a percentage by dividing the standard deviation associated with the impact category by the respective mean result score. This value provides an indication of how uncertain the average result is.

(v) The compliance between analytical and sampled variance to the concept of additivity of variances was tested by applying Eq. (12) for the individual parameters of each case study scenario and all impact categories. This was

performed based first on the analytical method and then on the sampling populations resulting from the Monte Carlo simulations.

(c) Discernibility analysis based on the pair-wise difference between Monte Carlo results was carried out with varying number of simulation runs (N) and number of parameters included in the simulation (*r*).

4 Results

The discussion of results focuses mainly on scenario 1 for illustrative purposes, since similar behaviour was observed also for the two other scenarios in all steps of the methodology. Any difference between the three scenarios is specified when needed. Tables and figures regarding scenario 2 and 3 can be found in the Supporting Information.

4.1 LCA results and sensitivity

Figure 1 shows the normalized impact scores for all scenarios and impact categories. Negative values indicate savings, while positive values indicate impacts. The magnitude of the results scores varies between impact categories, depending on scenario and dataset choices. The impact categories with the highest overall PE scores are GWP, HTnc, ME, ET and RDfos. An example of how processes contribute to the net impacts for these impact categories is provided in Figure 2. A detailed contribution analysis describing the remaining impact categories is summarized in the Supporting Information.

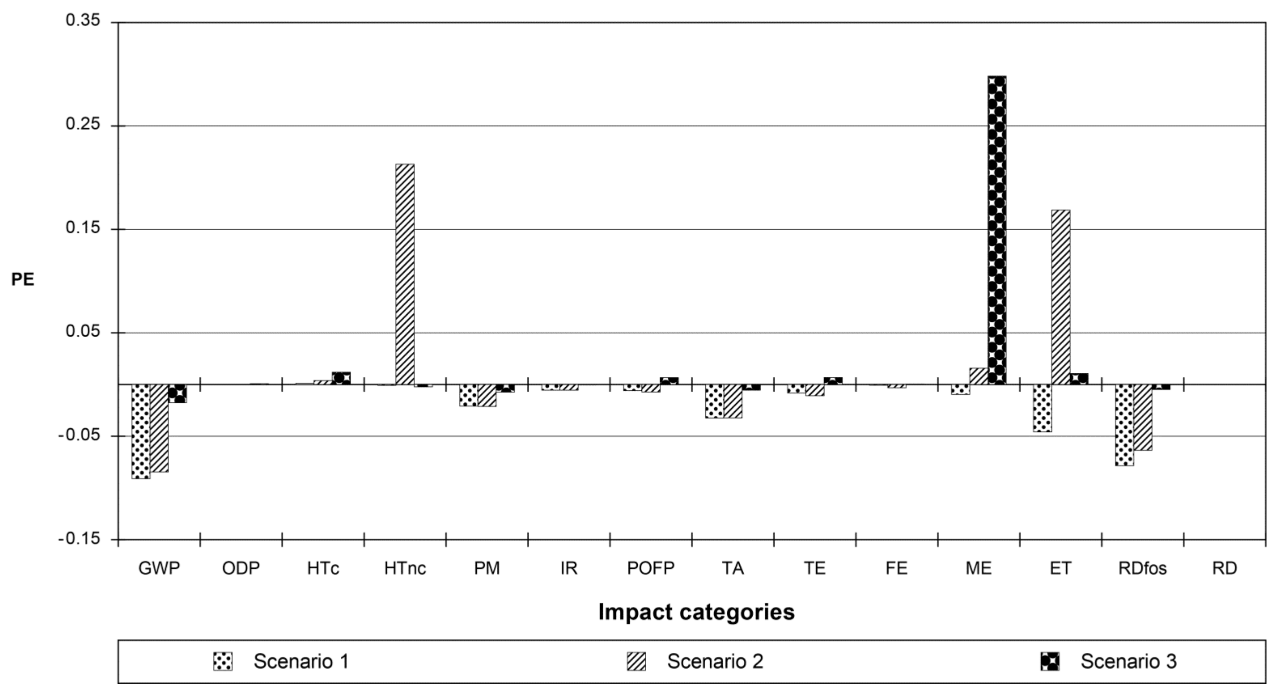

Fig. 1 Normalized impact scores for the three waste management scenarios. The impact categories are: climate change (GWP), stratospheric ozone depletion (ODP), human toxicity, cancer effects (HTc), human toxicity, non-cancer effects (HTnc), particulate matter (PM), ionizing radiation (IR), photochemical ozone formation (POFP), terrestrial acidification (TA), terrestrial eutrophication (TE), freshwater eutrophication (FE), marine eutrophication (ME), freshwater ecotoxicity (ET), fossils depletion (RDfos), metals/minerals depletion (RD).

The contribution analysis allowed selection of a total of eighty parameters for each scenario, including aspects such as waste characteristics (relevant for input specific emissions), process specific features of technologies, fuel consumption, distances driven, recycling and recovery rates. The amount of the most abundant waste fractions was also parameterized, maintaining the same reference flow. A complete list of the parameters selected based on the contribution analysis is available in the Supporting Information.

Table 1 provides the results of the perturbation analysis as SR and SC for the selected sensitive parameters and impact categories for scenario 1. The parameters are shown in Table 1 in hierarchical order according to their sensitivity, which can be positive or negative depending on the sign of the result score. The SCs cannot be directly compared, having different units. The SRs have the same unit, but caution needs to be paid for comparisons across scenarios and impact categories. Scenario 1 presents overall low SRs with values above 2 (corresponding to a variation in results of over 20 % with a 10 % variation in parameters) for the HTnc, IR, ME and FE impact categories. These impact categories also show the highest SRs for scenario 2. Scenario 3 presents somewhat higher SRs compared to S1 and S2, with the highest SR of 11 in the ET impact category (data not shown). The differences in SR values are due to the fact that the delta between results generated in the OAT is divided by the original result score, as shown in Eq. (2). Therefore, impact categories with small-magnitude scores are likely to have higher SR values with the same OAT delta between results. For this reason, the choice of the most sensitive parameters should not be based on comparisons between SRs of different impact categories, and the effect of parameter variations should be carefully evaluated within the individual impact categories and scenarios.

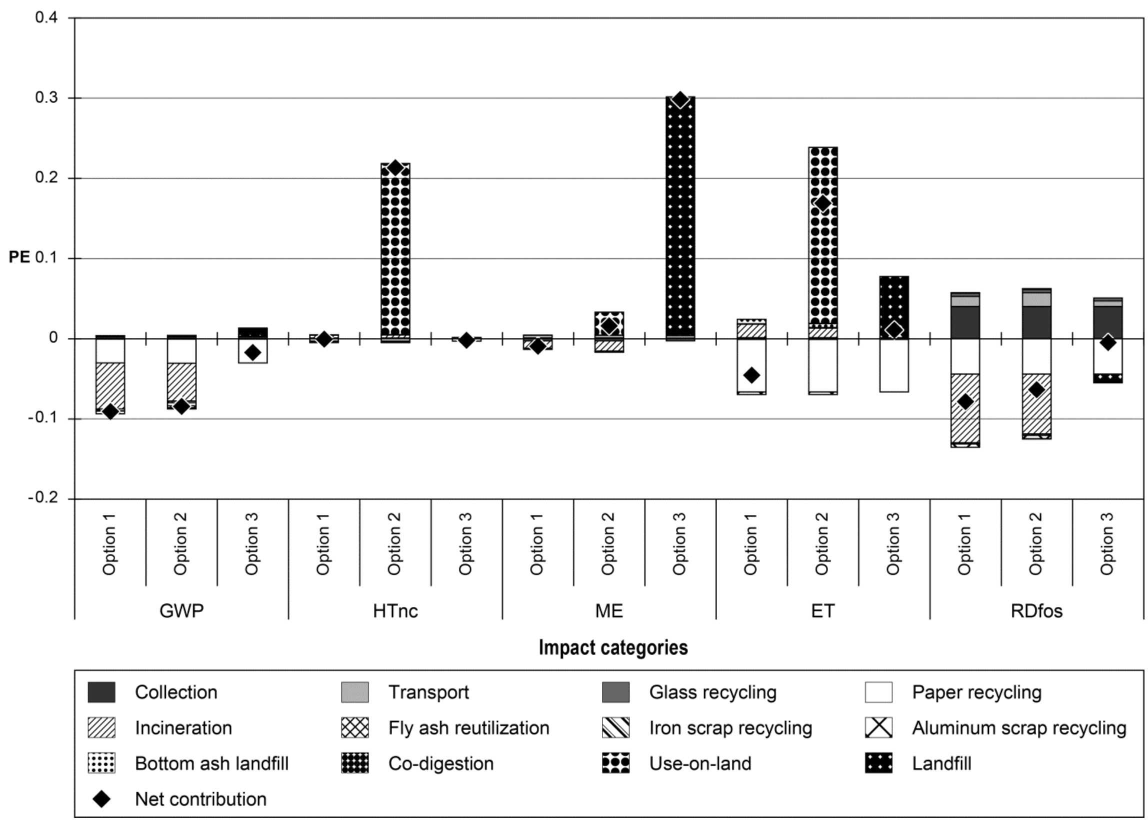

Fig. 2 Contribution analysis of the normalized results for selected impact categories.

Table 1. Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters in scenario 1 and selected impact categories. The sampled uncertainty results from increasing number of Monte Carlo sampling points (N). Variances for "Amount, vegetable waste" could not be obtained through Monte Carlo sampling as the random sampling would result in different reference flows for all the simulated results, thereby not allowing comparability.

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo					
				$N=10^3$		$N=10^4$		$N=10^5$	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Global warming potential (GWP)									
Electricity recovery	5.9E-01	-2.4E-01	**7.1E-06**	7.4E-06	*5%*	7.2E-06	*2%*	7.1E-06	*0%*
Water content, vegetable waste	-5.1E-01	6.0E-02	**5.4E-06**	5.0E-06	*-8%*	5.2E-06	*-4%*	5.1E-06	*-5%*
Paper recycling	4.0E-01	-4.4E-02	**3.4E-06**	3.2E-06	*-4%*	3.5E-06	*3%*	3.4E-06	*0%*
Heat recovery	3.3E-01	-4.1E-02	**2.3E-06**	2.3E-06	*2%*	2.2E-06	*0%*	2.3E-06	*0%*
Segregated paper	3.2E-01	-5.0E-04	**2.1E-06**	2.0E-06	*-4%*	2.1E-06	*1%*	2.1E-06	*0%*
Amount, vegetable waste	-2.8E-01	9.6E-05	**1.6E-06**	-	-	-	-	-	-
Water content, animal food waste	-1.5E-01	2.4E-02	**4.6E-07**	4.6E-07	*-1%*	4.4E-07	*-4%*	4.4E-07	*-4%*
Particulate matter (PM)									
Electricity recovery	6.0E-01	-5.7E-02	**4.0E-07**	4.2E-07	*6%*	3.9E-07	*-1%*	3.9E-07	*-1%*
Water content, vegetable waste	-5.0E-01	1.4E-02	**2.7E-07**	1.9E-07	*-32%*	1.9E-07	*-31%*	1.9E-07	*-31%*
Paper recycling	3.8E-01	-9.5E-03	**1.6E-07**	1.6E-07	*-3%*	1.6E-07	*2%*	1.6E-07	*1%*
Segregated paper	3.0E-01	-1.1E-04	**9.7E-08**	9.5E-08	*-2%*	9.8E-08	*1%*	9.7E-08	*0%*
Amount, vegetable waste	-2.7E-01	2.1E-05	**8.0E-08**	-	-	-	-	-	-
NOx incineration	-2.2E-01	5.5E+00	**5.5E-08**	5.6E-08	*2%*	5.5E-08	*0%*	5.5E-08	*-1%*
Heat recovery	1.6E-01	-4.7E-03	**2.9E-08**	2.9E-08	*0%*	2.8E-08	*-3%*	2.8E-08	*-2%*
Water content, animal food waste	-1.5E-01	5.4E-03	**2.4E-08**	1.7E-08	*-29%*	1.6E-08	*-32%*	1.7E-08	*-31%*
Marine eutrophication (ME)									
NOx incineration	-3.1E+00	3.5E+01	**2.2E-06**	2.2E-06	*3%*	2.1E-06	*-1%*	2.2E-06	*0%*
Heat recovery	2.7E+00	-3.6E-02	**1.7E-06**	1.8E-06	*1%*	1.7E-06	*0%*	1.7E-06	*1%*
Water content, vegetable waste	-2.6E+00	3.3E-02	**1.6E-06**	1.1E-06	*-31%*	1.2E-06	*-27%*	1.1E-06	*-28%*
Electricity recovery	1.3E+00	-5.8E-02	**4.1E-07**	4.4E-07	*7%*	4.2E-07	*2%*	4.1E-07	*0%*
Amount, vegetable waste	-8.8E-01	3.2E-05	**1.8E-07**	-	-	-	-	-	-
Water content, animal food waste	-7.9E-01	1.3E-02	**1.4E-07**	1.0E-07	*-27%*	1.0E-07	*-29%*	1.0E-07	*-28%*
Heating value, vegetable waste	5.9E-01	-3.1E-04	**8.0E-08**	8.3E-08	*3%*	8.0E-08	*0%*	8.0E-08	*0%*
Heating value, plastic waste	5.7E-01	-1.5E-04	**7.4E-08**	7.7E-08	*4%*	7.4E-08	*0%*	7.3E-08	*0%*

4.2 Uncertainty propagation

4.2.1 Single parameters

Table 1 compares by percentage difference single-parameter variances obtained analytically and by Monte Carlo sampling. The values shown refer to the same selected parameters and impact categories discussed in section 4.1. Results for all impact categories are provided in the Supporting Information.

Analytical uncertainty values were calculated with Eq. (7). The results follow the same hierarchical order of the SRs due to the common uncertainty range chosen for the analysis. The Monte Carlo results were obtained running the uncertainty analysis selecting one parameter at a time. The two methods differ in terms of time required for the calculation: for the analytical method, results were obtained in a few seconds using a simple spreadsheet, while time ranged from seconds to tens of minutes for the Monte Carlo simulations (depending on the parameter and impact category). The variances obtained with Monte Carlo show similar values to those obtained analytically. For most parameters, the average difference from the analytical value was reduced from around 10 % for N=1000 to close to 0 % with N=100000. When the number of samples is higher, the difference between results reduces considerably due to the reduced "randomness" brought by larger number of samples within the distribution. Additionally, the reduction of the percentage difference appears not to be related to the SR nor SC of the parameter.

For a few parameters and impact categories, differences of the order of 30 % between the analytical and the sampled values were observed (increasing N only marginally decreased the differences). These specific parameters are related to the moisture content of the waste (S1-S3) and to the landfill characteristics (S3). In both cases, differences are due to a high interdependency between parameters that is specific to waste LCA studies. In waste modelling, the moisture content is analytically characterized as a complementary of the contents of total solids and affects the chemical composition of the waste modelled in the scenarios. Thus, varying the water content of LCAs based on waste sampling data can cause variations of the chemical composition. Likewise, in case of parameters describing landfill characteristics, e.g. leachate production and emissions to the environment may be interdependent. Hence, the calculated SCs reflect variations that are a consequence of correlations, while the input variance required to obtain the analytical uncertainty refers to one parameter only. Potentially, also the Monte Carlo results can be misleading. The simulation independently propagates the uncertainties of individual parameters, while correlated results would be visible only by implementing multivariate distributions (Bojacá and Schrevens 2010). This behaviour does not always occur with all water content-related parameters, but only for those impact categories that are affected by variations of the waste composition, e.g. the toxicity categories.

The analytical method was considerably faster to implement than Monte Carlo sampling. The values obtained for the single parameters suggest that the analytical method can provide a good approximation of the variance of most parameters in the LCA model. The results of the Monte Carlo sampling better fit the analytical scores with higher number of sampling points; this, however, requires longer simulation times and manual selection of the parameters for the simulations. Moreover, the analytical calculation would respond quickly to a change of distribution type and uncertainty range of the parameters. With different uncertainty ranges, the hierarchy of analytical uncertainties would also change, representing the *importance* of the parameters within the scenarios. Uncertainty associated to parameters with correlations can only be approximated by both methods. The analytical method further allows evaluation of potential contribution to variances caused by changes in the waste composition; this is currently not possible with Monte Carlo simulations as the random sampling may result in changes to the reference flow and thereby the functional unit of the scenarios. However, for most of the tested impact categories the analytical method demonstrated that the waste composition was highly relevant for the impact results.

4.2.2 All parameters

Table 2 provides a selection of the uncertainty analysis results for all parameters in scenario 1 and all impact categories. When all parameters are included in the uncertainty propagation, the resulting variance value is a single score representing the total parametrical variance for the scenario. The results thus comply with the concept of additivity of variances explained in the methodology section. The analytical variance was calculated with Eq. (8) for each impact category and results are shown in the upper part of Table 2. These values were compared to the normalized result scores by calculation of the CV with Eq. (13). The highest variation around the mean was observed for ME at 27 %. The lowest CVs were around 5 %.

For each impact category and Monte Carlo run, the lower part of Table 2 presents the difference between sampled variance and the analytical variance, and the associated CV. The mean values obtained from the Monte Carlo results show negligible differences with respect to the LCIA result scores (<0.5 %, data not shown). The difference between sampled an analytical variance was in average around 6 % for N=1000, about half of that observed in Table 1 for single parameters. Comparisons in literature between other analytical methods and Monte Carlo simulations showed similar outcomes. The same average difference within about 5 % for a full scenario was observed for Hong et al. (2010) and Heijungs and Lenzen (2014), while lower differences were found by Imbeault-Tétreault et al. (2013) and Groen et al. (2014). For increasing N, the differences with the analytical variances were reduced for most impact categories, except when the parameters were related to the moisture content of the waste. However, the Monte Carlo simulations indicated differences in variances of maximum 14 %, suggesting that the effect of interdependent parameters is "absorbed" when considering entire scenarios. The CVs based on Monte Carlo simulations showed marginal differences, within 1 %, with the CVs calculated from the analytical variance values.

In the case of uncertainty analysis for full parameter sets, the difference in the speed performance between the two uncertainty propagation methods was enormous, as also illustrated by Heijungs and Lenzen (2014). The analytical method only required summing of the values calculated with Eq. (7) in a spreadsheet, while the Monte Carlo simulations required manual selection of parameters and calculation times ranging from tens of minutes to hours, depending on the impact category.

Once again, the analytical variance provides results very similar to the ones of the Monte Carlo. The simulation results showed reduced differences from the analytical values with increasing number of sampling points. These observations are in accordance with the concept of additivity of variances, since the analytical values sufficiently well represent the total parametrical uncertainties of a scenario. The analytical uncertainty method can provide a fast approximation of the total scenario parametrical variance, useful for immediate determination of standard deviations for each impact result score.

Table 2. Variance obtained by analytical and sampling methods for waste management scenario 1. The Monte Carlo results were obtained for various numbers of sampling points (N).

		GWP	ODP	HTc	HTnc	PM	IR	POFP	TA	TE	FE	ME	ET	RDfos	RD
Analytical method															
Analytical variance	**[PE^2]**	**2.25E-05**	**1.01E-11**	**2.41E-09**	**1.29E-07**	**1.13E-06**	**6.70E-08**	**1.32E-06**	**3.45E-06**	**5.26E-06**	**1.91E-09**	**6.55E-06**	**2.23E-05**	**4.18E-05**	**1.34E-12**
Coefficient of variation	[%]	-5.2%	-4.8%	4.1%	-48.7%	-5.1%	-4.8%	-19.6%	-5.7%	-27.9%	-6.9%	-26.7%	-10.3%	-8.2%	-6.1%
Monte Carlo simulation															
Sampled variance [PE^2]	N=10^3	**2.38E-05**	**1.00E-11**	**2.53E-09**	**1.34E-07**	**1.08E-06**	**6.60E-08**	**1.15E-06**	**2.97E-06**	**4.59E-06**	**1.87E-09**	**5.72E-06**	**2.27E-05**	**4.07E-05**	**1.32E-12**
	N=10^4	**2.22E-05**	**1.00E-11**	**2.31E-09**	**1.21E-07**	**1.04E-06**	**6.66E-08**	**1.19E-06**	**2.99E-06**	**4.94E-06**	**1.95E-09**	**5.86E-06**	**2.25E-05**	**3.73E-05**	**1.36E-12**
	N=10^5	**2.22E-05**	**1.01E-11**	**2.34E-09**	**1.21E-07**	**1.03E-06**	**6.67E-08**	**1.21E-06**	**3.02E-06**	**4.77E-06**	**1.91E-09**	**6.04E-06**	**2.22E-05**	**3.90E-05**	**1.33E-12**
Difference of sampled variance from the analytical variance [%]	N=10^3	*5.7%*	*1.2%*	*5.0%*	*4.0%*	*4.6%*	*1.6%*	*13.2%*	*14.0%*	*12.7%*	*1.7%*	*12.6%*	*1.8%*	*2.7%*	*1.4%*
	N=10^4	*1.2%*	*1.0%*	*4.2%*	*6.0%*	*8.3%*	*0.6%*	*10.4%*	*13.5%*	*6.0%*	*2.3%*	*10.4%*	*0.9%*	*10.8%*	*1.7%*
	N=10^5	*1.4%*	*0.1%*	*2.9%*	*5.5%*	*8.9%*	*0.5%*	*8.2%*	*12.7%*	*9.2%*	*0.0%*	*7.7%*	*0.3%*	*6.7%*	*0.3%*
Coefficient of variation [%]	N=10^3	-5.4%	-4.8%	4.2%	-50.0%	-5.0%	-4.7%	-18.2%	-5.3%	-26.0%	-6.8%	-24.9%	-10.4%	-8.2%	-6.1%
	N=10^4	-5.2%	-4.8%	4.0%	-47.1%	-4.9%	-4.8%	-18.5%	-5.3%	-27.1%	-7.0%	-25.3%	-10.4%	-7.8%	-6.1%
	N=10^5	-5.2%	-4.9%	4.0%	-47.5%	-4.9%	-4.8%	-18.7%	-5.4%	-26.6%	-6.9%	-25.7%	-10.3%	-8.0%	-6.1%

The highest uncertainties around the mean result scores can thus be instantaneously quantified, e.g., with the CV (Eq. (13)) and by means of error bars. This is of great value in comparative LCAs, since the analytical method allows fast identification of the impact categories presenting potentially overlapping results and requiring discernibility analysis.

4.3 Global sensitivity analysis perspective

The variance associated with the single parameters was rank ordered (*r*) and a partial variance was calculated progressively for increasing *r* with Eq. (12). Figure 3 illustrates the behaviour of impact category results for the three scenarios. The *y* axis shows the percentage of the total analytical variance reached with the number of parameters included in the propagation (*r*) at the corresponding point of the *x* axis. It is evident that all impact categories have a similar behaviour with respect to the scenario uncertainty; most of the uncertainty could be represented by very few parameters. A high level of representation was reached within the ten parameters shown in the graph. In this case, six parameters represent a good compromise between the number of parameters selected for the representation and the average represented variance, which is about 90 % for all impact categories and waste management scenarios. Some impact categories show a clearly steeper behaviour, for example ODP for scenario 1 and 2. Table 3 summarises the highest-ranking parameters identified with the GSA framework and shows the associated percentage of represented analytical variance at the corresponding number of parameters included in the uncertainty propagation. White cells indicate the set of parameters that are required to reach 90% of represented uncertainty. Progressive determination of variances was also carried out with Monte Carlo simulations, confirming how the precision of the simulations increased with increasing number of samplings, ultimately reaching the analytical calculations. The Monte Carlo results fit well the analytical behaviour, and the uncertainty reaches an asymptotic behaviour within the limited number of parameters considered (see Supporting Information for details).

The analytically calculated uncertainty and a GSA perspective can be used to identify the parameters that are actually needed to appropriately represent the uncertainty in each impact category. The number of parameters depends on the scenario and the impact category and should be determined on a case-by-case basis. The focus on multiple impact categories in this study has demonstrated how the number of important parameters is limited as parameters are "shared" between impact categories. For scenario 1, considering the six highest ranking parameters in all impact categories corresponds to a total of ten parameters out of the initial eighty (in bold in Table 3). A significant simplification of the uncertainty representation.

Uncertainty "concentrated" in a few parameters highlights the vulnerability of the decisional process based on LCA results when, for example, a single external process carries the majority of the uncertainty associated with an impact category. A similar observation was highlighted also by Hong et al. (2010) indicating that some parameters could contribute with large shares (>75 %) to total the uncertainty in some impact categories. Figure 3 suggests that the uncertainty is controlled to a large extent by the 6 – 7 most important parameters within each impact category, while the remaining parameters contribute to a lower extent in reaching the asymptotical total variance. This confirms that when looking at the entire set of parameters, the error brought by the interdependent parameters is reduced when the parameters do not have a high scenario importance, while the error remains significant when the parameters are the one of the "important" parameters in an impact category.

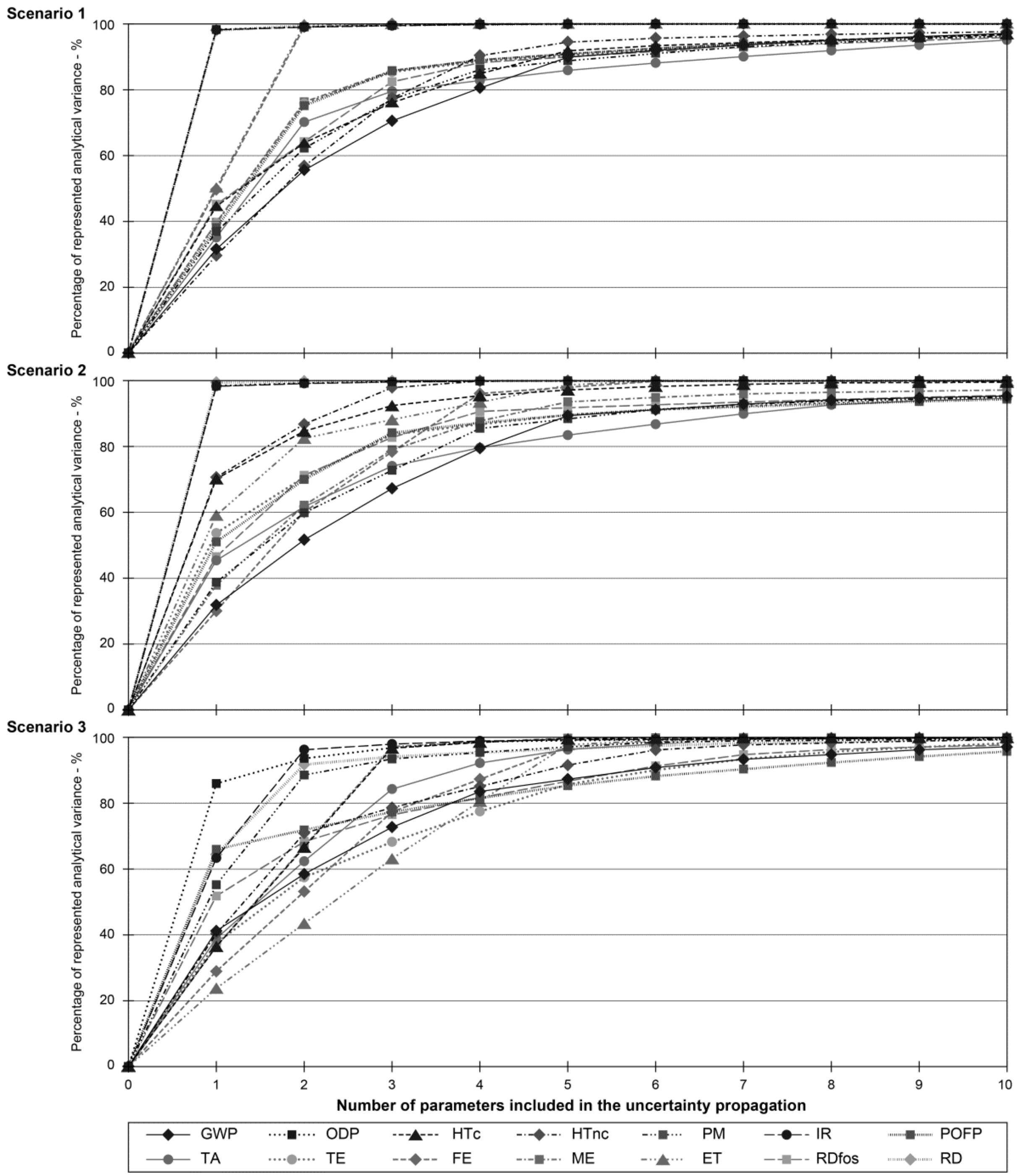

Fig. 3 Percentage of the total analytical variance reached with a variable number of parameters included in the propagation for the three waste management scenarios. The lines represent the impact categories.

Table 3. Ranking of parameters identified with the GSA framework and associated percentage of represented analytical variance for scenario 1 at the corresponding number of parameters included in the uncertainty propagation. White cells indicate the set of parameters that are required to reach 90% of represented uncertainty; parameters in bold are the subset of ten parameters governing most of the uncertainty in the scenario.

Impact category	**Number of parameters included in the uncertainty propagation** Parameter (*percentage of represented analytical variance*)									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
GWP	**Electricity recovery** *32%*	**Water content, vegetable waste** *56%*	**Paper recycling** *71%*	**Heat recovery** *81%*	**Segregated paper** *90%*	Water content, animal food waste *92%*	Heating value, vegetable waste *94%*	Heating value, plastic waste *95%*	Fossil carbon content, plastic waste *96%*	Heating value, animal food waste *97%*
ODP	**Aluminium recycling** *98%*	**Paper recycling** *99%*	**Segregated paper** *99%*	**Electricity recovery** *100%*	**Water content, vegetable waste** *100%*	Water content, animal food waste *100%*	Heating value, vegetable waste *100%*	Heating value, plastic waste *100%*	Electricity consumption, paper recycling *100%*	Heating value, animal food waste *100%*
HTc	**Electricity recovery** *45%*	**Paper recycling** *64%*	**Segregated paper** *76%*	**Water content, vegetable waste** *85%*	**Aluminium recycling** *92%*	**Gravel recycling** *93%*	Heating value, vegetable waste *94%*	Heating value, plastic waste *95%*	**Glass recycling** *96%*	Steel recycling *97%*
HTnc	**Electricity recovery** *30%*	**Paper recycling** *57%*	**Segregated paper** *77%*	**Water content, vegetable waste** *90%*	**Aluminium recycling** *94%*	**Water content, animal food waste** *96%*	Heating value, vegetable waste *96%*	Heating value, plastic waste *97%*	Steel recycling *97%*	**Glass recycling** *98%*
PM	**Electricity recovery** *37%*	**Water content, vegetable waste** *62%*	**Paper recycling** *77%*	**Segregated paper** *86%*	**NOx incineration** *89%*	**Heat recovery** *91%*	**Water content, animal food waste** *93%*	**Aluminium recycling** *94%*	Heating value, plastic waste *96%*	Heating value, vegetable waste *96%*
IR	**Aluminium recycling** *98%*	**Paper recycling** *99%*	**Segregated paper** *99%*	**Electricity recovery** *100%*	**Water content, vegetable waste** *100%*	**Gravel recycling** *100%*	**Water content, animal food waste** *100%*	Heating value, vegetable waste *100%*	Heating value, plastic waste *100%*	Heating value, animal food waste *100%*
POFP	**NOx incineration** *38%*	**Heat recovery** *75%*	**Water content, vegetable waste** *86%*	**Electricity recovery** *89%*	**Water content, animal food waste** *91%*	Heating value, vegetable waste *93%*	Heating value, plastic waste *94%*	**Glass recycling** *95%*	Heating value, animal food waste *96%*	NOx paper recycling *96%*
TA	**Heat recovery** *35%*	**Water content, vegetable waste** *70%*	**Electricity recovery** *80%*	**NOx incineration** *83%*	**Glass recycling** *86%*	**Water content, animal food waste** *88%*	**Aluminium recycling** *90%*	**Segregated glass** *92%*	**Paper recycling** *94%*	Heating value, vegetable waste *95%*
TE	**NOx incineration** *39%*	**Heat recovery** *76%*	**Water content, vegetable waste** *85%*	**Electricity recovery** *89%*	**Water content, animal food waste** *90%*	Heating value, vegetable waste *92%*	Heating value, plastic waste *94%*	**Glass recycling** *95%*	Heating value, animal food waste *96%*	NOx paper recycling *96%*
FE	**Glass recycling** *50%*	Segregated glass *99%*	**Paper recycling** *100%*	**Segregated paper** *100%*	**Gravel recycling** *100%*	**Electricity recovery** *100%*	**Aluminium recycling** *100%*	Fuel consumption residual waste collection *100%*	**Water content, vegetable waste** *100%*	Distance, residual waste transportation *100%*
ME	**NOx incineration** *40%*	**Heat recovery** *76%*	**Water content, vegetable waste** *86%*	**Electricity recovery** *89%*	**Water content, animal food waste** *91%*	Heating value, vegetable waste *93%*	Heating value, plastic waste *94%*	Glass recycling *95%*	Heating value, animal food waste *96%*	NOx paper recycling *96%*
ET	**Paper recycling** *50%*	**Segregated paper** *100%*	Aluminium recycling *100%*	**Electricity recovery** *100%*	**Glass recycling** *100%*	Segregated glass *100%*	Zinc emission, iron recycling *100%*	Water content, plastic waste *100%*	**Water content, vegetable waste** *100%*	Fuel consumption residual waste collection *100%*
RDfos	**Electricity recovery** *45%*	**Water content, vegetable waste** *64%*	**Paper recycling** *82%*	**Segregated paper** *88%*	Fuel consumption residual waste collection *90%*	**Water content, animal food waste** *92%*	Distance, residual waste transportation *93%*	Fuel consumption, residual waste transportation *94%*	Heating value, vegetable waste *95%*	Heating value, plastic waste *96%*
RD	**Gravel recycling** *98%*	**Water content, vegetable waste** *100%*	**Water content, animal food waste** *100%*	Water content, yard waste *100%*	Water content, diapers waste *100%*	Water content, paper waste *100%*	Water content, advertisements waste *100%*	Water content, plastic waste *100%*	Water content, dirty paper waste *100%*	Water content, newsprints waste *100%*

4.4 Discernibility analysis

Table 4 reports the results of the discernibility analysis performed on scenario 1 versus scenario 2. Comparisons with scenario 3 and between scenario 2 and 3 were not relevant since variations around mean result values were not overlapping; this information is provided by the standard deviations calculated from the CVs of Table 2. Discernibility analysis requires a result population obtained by the Monte Carlo sampling. Here, impact scores are obtained based on modelling with 6 and 80 parameters included in the simulation as well as different numbers of sampling points in the Monte Carlo.

The six parameters identified in Section 4.3 were sufficient to carry out the discernibility analysis and provided similar results as when all 80 parameters were included. Moreover, the results differ only by 1 % between the various Monte Carlo simulations with different numbers of sampling points. Performing discernibility analysis only on the parameters identified as important with an analytical uncertainty propagation and a global sensitivity perspective is much faster and efficient. Only a small number of simulations is required to understand in how many cases scenario 1 is preferable over scenario 2, thereby shortening the computational time that is typically required and solving the time-consuming nature of the discernibility analysis addressed by Heijungs and Kleijn (2001).

Regarding shared parameters and processes between scenarios, the analytical method suggests that it is very unlikely that parameters might have the same influence in two scenarios, since this *importance* is a combination between given parametrical uncertainty, which might be the same, and sensitivity, which will likely be different. Therefore, discernibility analysis can estimate only in how many cases one scenario is preferable over another, or the uncertainty of the difference between scenarios, but not totally eliminate the influence of shared parameters.

5 Discussion

5.1 Combining SCs with analytical uncertainty propagation

The results confirmed previous findings in literature regarding comparison between analytical and sampling methods. The analytical method provides good approximation of the sampled results while being substantially simpler, as also observed by Hong et al. (2010). The differences are mainly related to simulation speed and the type of results provided (Heijungs and Lenzen 2014; Groen et al. 2014). For either propagation methods, the contributions and sensitivity analysis steps are fundamental, as selection of parameters for the uncertainty analysis is traditionally subjective. Application of the dedicated waste LCA model EASETECH was essential in this context, since the model allows tracking of impact contributions from substances and material flows, in addition to internal and external processes. The parameterization feature allowed easy switching from OAT to uncertainty propagation with the Monte Carlo.

For all scenarios, the SC (Eq. (5)) was found to provide valuable representations of the derivative in the error propagation formula (Eq. (4)), with differences from the results of Monte Carlo sampling within the error ranges of other analytical propagation methods. Moreover, by utilizing the SC, the proposed analytical propagation method therefore compels the practitioner to carry out a thorough sensitivity analysis. The mathematical calculations required for the uncertainty analysis are considerably simplified, thereby increasing transparency of the analysis: LCA practitioners may easily connect the single parameters to their uncertainty, and evaluate the uncertainty results as a consequence of the

Table 4. Discernibility analysis results for selected impact categories in the comparison between scenario 1 and scenario 2. Comparisons are carried out for different number of parameters (i) included in the Monte Carlo simulation and sampling points (N).

	GWP	**ODP**	**PM**	**IR**	**POFP**	**TA**	**TE**	**RDfos**	**RD**
i=6									
$N=10^3$	85%	42%	41%	42%	15%	50%	16%	97%	91%
$N=10^4$	86%	41%	42%	42%	14%	53%	16%	97%	91%
$N=10^5$	85%	41%	42%	42%	14%	53%	16%	97%	91%
i=80									
$N=10^3$	84%	41%	43%	42%	15%	50%	17%	96%	92%
$N=10^4$	86%	41%	42%	42%	15%	51%	17%	97%	90%
$N=10^5$	85%	42%	43%	42%	15%	52%	17%	96%	91%

The choice of this analytical method allows propagating uncertainties up to the normalization level, because the SCs were calculated from the normalized result scores. In the same fashion, uncertainties can be propagated for the characterized impacts when SC is calculated from the characterized result scores. While expressing an uncertainty for the normalization factor in the SC formula could be implemented easily, including the characterization factors in the SC formula (Eq. (5)) would not be possible in the same simplified fashion. For this purpose, the matrix LCA formulation suggested by Heijungs (2010) would be more appropriate.

The assumption of linearity of model equations is considered reasonable. The EASETECH model is based on a layered computational structure (Clavreul et al. 2014) and the inventory, the characterization and normalization layers are based on linear equations. Non-linearity only rarely occurs in the material flow layer, and the relatively small differences between sampling and analytical methods' results do not warrant a more complicated method.

The assumption of independent uncertainties is not valid in cases involving interdependencies between parameters. The results of the analytical uncertainty analysis diverge from those of the Monte Carlo. However, both methods are based on the hypothesis of independent variables, and both can only provide an approximated value for the uncertainty when parameters are correlated. The practitioner could address this by changing the modelling of processes or technologies involving interdependent parameters (thereby essentially "de-coupling" the parameters) or further investigating the correlation. In the latter case, correlation would enlarge the Monte Carlo sampling space, by rotating the main axes of the distribution away from the coordinate axes and thus elongating the probability distribution (Bojacá and Schrevens 2010). Huijbregts et al. (2003) suggested identifying the parameters that contribute most to the output uncertainty before carrying out a correlation analysis. However, this would separate the correlation analysis from the global perspective, where the correlation plays a fundamental role in the definition of a parameter's importance (Eq. (9)).

The results of Table 2 and Figure 3 comply with the concepts of additivity of variances and of the total parametrical scenario variance. Thereby, the GSA perspective could be applied allowing a unification of sensitivity and uncertainty concepts. The results of the global importance analysis can be used to reduce the number of parameter uncertainties needed in the uncertainty propagation. Traditionally, the number of parameters has been reduced only based on the sensitivity analysis, thereby excluding potential importance of very uncertain parameters. The focus on multiple impact categories confirmed that the threshold for selection of important parameters should be based on multiple impact categories, since this allows representation of a large proportion of variability in impact results based on a limited number of parameters.

5.2 Applicability to other cases and validity of the results shown

As anticipated in 2.2.1, the presented analytical method is not limited to a specific probability distribution type. Any differences between distribution types are contained in the expression of the input variance assigned to the model parameters (Eq. (7), V_{input}). Although the percent differences presented in the results refer to the specific assumptions of 10 % uncertainty and normal distributions, compliance between the analytical and Monte Carlo sampling methods and to the concepts of additivity of variances was observed for higher uncertainty ranges and other distribution types, including cases with extremely skewed distributions and mixed uncertainty ranges and distribution choices (details in the Supporting Information). When the uncertainty range is common between all parameters, their resulting hierarchy and contribution to the output variance is unchanged, allowing the selection of the same important parameters presented in the results in the article (Table 3). When uncertainty ranges and distribution types are mixed, the compliance to the GSA concepts is still verified. The hierarchies and contribution to variances change, but a selection of a smaller set of fifteen parameters was found sufficient to carry out a discernibility analysis across fourteen impact categories.

The freedom of choice between distribution types is especially useful in case of waste LCAs where negative values often should be excluded and log-normal distributions would provide better representation of uncertainties, e.g. consumption of materials and emissions (Clavreul et al. 2012). As described in existing literature, possibility theory would be more suited to represent characteristics of waste management systems typically characterized by qualitative data. In such cases, information from fuzzy sets could be converted to, e.g., uniform probability distributions, and the SC method could still provide an approximated result of the uncertainty.

5.3 Revised step-wise approach for quantitative uncertainty assessment

Based on the results, a modification to the existing step-wise approach for quantitative uncertainty assessment of waste LCAs (Clavreul et al., 2012) is suggested. The revised step-wise approach, compared to the traditional and the tested approach, is presented in Figure 4. The well-established first steps of the traditional approach are still essential. A contribution analysis (Step 0) is fundamental to correctly parameterize and include the most contributing features of the system for the sensitivity analysis (Step 1). Calculation of SRs provides a quick ranking of parameters according to sensitivity, which should be analysed contextually within all impact categories and case study scenarios. High ranking parameters might foster further data collection, especially in preparation for the uncertainty analysis. These conventional steps constitute also the basis for applying the GSA framework. The SCs, obtained with a sufficiently small percentage

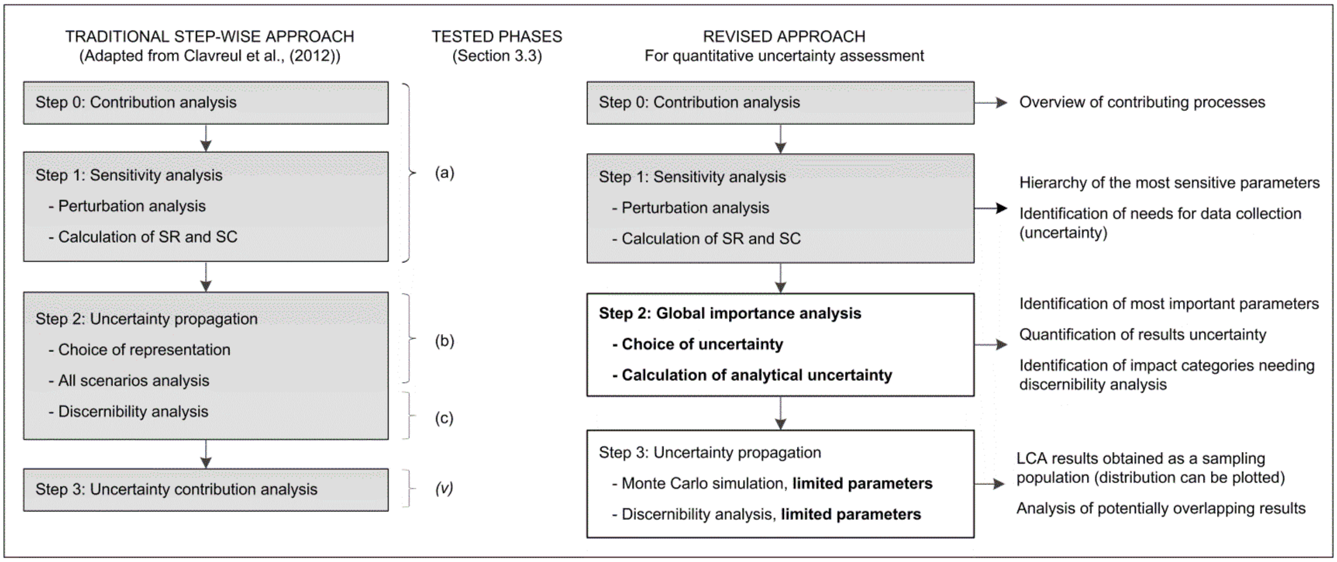

Fig. 4 Revised sequential approach for quantitative global importance and uncertainty analysis compared to a traditional step-wise approach and the tested phases.

variation in the perturbation calculation, provide a "slope factor" to which the input uncertainties associated with each parameter can be multiplied in the global importance analysis (Step 2). The sensitivity and uncertainty terms can thus be combined and the parameters systematically ranked according to their importance. As highlighted in Meinrenken et al. (2012) this could be carried out concurrently to the data gathering phase. Additionally, this step provides quantification of the variability (e.g. CVs, Table 2) and reliability (e.g. ODP uncertainty depending on just one parameter, Figure 3) of the result scores, with negligible difference to Monte Carlo simulations. In comparative LCAs, the LCA practitioner could identify at this stage which impact categories would require a Monte Carlo simulation for the discernibility analysis. Hierarchically ranking the parameters according to importance allows systematic selection of how many parameters (*r*) are required to reach a sufficient percentage of representativeness of the uncertainties in each impact category. Then, the uncertainty propagation (Step 3) can be carried out just for these few parameters and with a limited number of Monte Carlo runs, for the discernibility analysis or representation of the LCA results by probability distribution functions. Within the impact categories for which a discernibility analysis is necessary, it is still possible to perform a combined sensitivity analysis as suggested by Clavreul et al. (2012).

6 Conclusions

A traditional step-wise approach for quantification of uncertainty in LCA was applied in a comparative study including three full-scale waste management systems modelled with the EASETECH LCA model. Uncertainties were propagated by an approximated analytical approach as well as with Monte Carlo simulation. Uncertainty propagation both for single parameters and full parameter sets (eighty) over fourteen ILCD recommended impact categories was included. The analytical method was examined in a Global Sensitivity Analysis (GSA) framework and critically important parameters were selected for completion of discernibility analysis for the specific impact categories and scenarios where results were potentially overlapping. The proposed analytical method for uncertainty propagation provided a transparent and simplified mathematical formulation as far as the normalized result level. The analytical method was evaluated against alternative Monte Carlo sampling and provided quantitatively similar results, but with considerably smaller computational efforts. The law of total variance and application of the GSA perspective played a pivotal role for simplification of uncertainty quantification by the proposed method. It was demonstrated that only few parameters are needed to represent most of the uncertainty in a scenario. The selection of these critical parameters should be carried out contextually to the system modelled and considering multiple impact categories. Consequently, research and efforts to minimise uncertainties can be focused on the important parameters, while other parameters can be fixed within an appropriate range without compromising the LCA results. This was further confirmed by discernibility analysis, which provided the same results based only on the few critical parameters identified through the global importance analysis. A new step-wise approach for uncertainty quantification was proposed to improve reliability, transparency and credibility of LCA practices. The waste management system modelled functioned as a real-scale case, suggesting that the presented approach constitutes a systematic method for quantification of the full importance of parameter sensitivity and uncertainty, applicable to any LCA study.

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Supporting Information for:

"A GLOBAL APPROACH FOR SPARSE REPRESENTATION OF UNCERTAINTY IN LIFE CYCLE ASSESSMENTS OF WASTE MANAGEMENT SYSTEMS"

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Summary

This supporting information describes the Life Cycle Assessment (LCA) case study modelled in the article. Section SI.1 provides a thorough description of the waste management scenarios and inventories of the chosen data and technologies. Sections SI.2 and SI.4 – SI.6 provide the complete range of results (Tables and Figures) obtained from testing the methodology presented in the article on the case study. SI.3 contains a brief literature review and guide on how to provide input uncertainty for parameters in the model. Finally, in SI.7 is discussed in detail the applicability of the method presented in the article to other cases of uncertainty ranges and distribution types.

Contents

SI.1 LCA case study

A hypothetical waste-LCA case study was set up to in order to investigate the sensitivity and uncertainty analysis methods addressed in the paper. The emphasis was placed on the methodological aspects rather than on intense data collection, although replicating a real case modelling size. The case study simulates three scenarios for the management of household waste from single family houses in Denmark in 2013. The systems modelled are partly based on a project conducted jointly by DTU Environment and COWI for the Danish Environmental Protection Agency (EPA) focusing on environmental and socio-economic opportunities for increasing the recycling of paper, plastic, metal and organic waste from household waste (Jensen et al. 2013).

Modelling framework

Goal

The LCA wants to provide an example of a real-size comparative assertion of the total environmental impacts associated with three treatment alternatives for single-family household waste in Denmark.

The purpose is to assess which solution between scenario 1, 2 and 3 performs better from an environmental point of view on a wide range of impacts and to test sensitivity an uncertainty analysis practices on vast scenarios characterized by different technologies. The model derives from a project originally commissioned by the Danish EPA, but is set up to test LCA methodological aspects. For this reason, a limit of the study is that it does not focus on data collection and that it assumes that the chosen processes and datasets comply with the quality standard requirements of a real-case commissioned waste-LCA. Data will be disclosed to the public through the journal publication as if the study would lead to a decision between the three waste management scenarios, but only mimicking one of the usual goals of this type of waste-LCAs. The technical targeted audience is composed by LCA experts and waste management professionals specialized in LCA. Although being just a case study for testing a methodology, the life cycle is intended for decision support and involves consequences that result in additionally installed or additionally decommissioned equipment / capacity outside the foreground system of the analysed system. Consequently, the decision context falls within Situation B (meso / macro level decision support for technology scenarios) according to European Commission (2010).

The LCA study did not undergo peer review, being only an example of a comparative assertion to be disclosed to the public. However, the reviewing process was implemented on the project on which the LCA model is based.

As far as the LCI modelling principle is concerned, it was chosen a consequential approach. Multi-functionality in the model is addressed by substitution / system expansion.

Scope

The functional unit is defined as follows: source segregation, collection and treatment of 1000 kg of single-family household waste produced in Denmark in the year 2013, including upstream and avoided processes.

The time horizon of the LCA is 100 years. The assessment includes consumption of energy and resources for collection, treatment and managing of the residues, emissions to air / water / soil, upstream processes (i.e. processing of materials for utilization) and avoided processes (i.e. avoided production of primary materials and energy substituted by the residues). Marginal technologies for energy substitution are selected as follows: coal for electricity and marginal average for production of thermal energy (based on combustion of waste, bio fuels, surplus heat and oil) in Denmark for heat. Construction and decommissioning of infrastructure, buildings, machinery, etc. were excluded from the assessment. The geographical scope is Denmark. The study is carried out with the waste-LCA software EASETECH (Clavreul et al. 2014). The material fractions, chemical composition, and processes are taken from EASETECH database and are described in the following sections. Waste composition and material fractions refer to Riber et al. (2009). Differences from the processes in the library are applied as in Jensen et al. (2013). The impact categories and the normalization factors utilized for the study are listed in Table S1. Contrarily to Jensen et al. (2013), the reference energy system for electricity is the Danish marginal average for the reference year 2006 (based on coal), while heat is based on district heating with reference year 2012.

LCA model in EASETECH

Waste generation

The case study is based on household waste generated by single family houses in Denmark in 2013. The composition of the waste stream is shown in Table S2. The waste is subdivided into 48 material fractions in accordance with the EASETECH library, which contains default data for the chemical composition for each fraction following Riber et al. (2009). The subdivision of the waste fractions is based on Jensen et al. (2013).

Systems modelled

The case study models three alternative waste management solutions. These three scenarios are schematized in Figure S1. The common features are shown in the top part of the table (a) and comprise generation, source segregation, collection and treatment of the recyclable fractions, which are paper and glass. Scenario 1 (b) incinerates the residual waste and recovers fly ashes and metal scraps, while bottom ashes are deposited in a mineral landfill. Scenario 2 (c) adds a source segregated stream for organic waste, which is co-digested with manure. The digestate is consequently applied on land. Residues from the treatment of the organic fraction and from source sorting are incinerated in the same fashion as (b). Scenario 3 (d) is characterized by landfilling the whole residual stream from source segregation. This third scenario was not present in Jensen et al. (2013) and was set up in order to test the uncertainty method on a scenario with higher technological differences than the first two. The stored emissions are drawn in grey since they are not taken into account by the temporal scope of the study. Figures S2 – S4 show the models in the EASETECH software window.

The material generation is common between the three scenarios, while differences arise for the source sorting step. Scenario 1 and scenario 3 are based on the source sorting of only paper and glass, while the residual waste is routed to treatment. The source segregation scheme is shown in Table S3. Scenario 2 is based on the additional source sorting of organic waste. Details are provided in Table S4. The source segregation percentages are based on Jensen et al. (2013).

Table S1. Characterization (*midpoint*) and normalization references utilized in the case study

Impact Category	Acronyms	Recommended default LCIA method	Indicator	Recommended in ILCD	Source	Reference year	Normalisation references	Units
Climate change	GWP	Baseline model of 100 years of the IPCC (IPCC 2007)	Radiative Forcing as Global Warming Potential (GWP 100)	Yes	ILCD	2010	8.10E+03	kg-CO2eq /person
Stratospheric ozone depletion	ODP	Steady-state ODPs 1999 as in WMO assessment (WMO 1999)	Ozone Depletion Potential (ODP)	Yes	ILCD	2010	4.14E-02	kg-CFC-11eq/person
Human toxicity, cancer effects	HTc	USEtox model (Rosenbaum et al. 2008)	Comparative Toxic Unit for humans (CTUh)	Yes	ILCD	2010	5.42E-05	cases/person
Human toxicity, non-cancer effects	HTnc	USEtox model (Rosenbaum et al. 2008)	Comparative Toxic Unit for humans (CTUh)	Yes	ILCD	2010	1.10E-03	cases/person
Particulate matter/Respiratory inorganics	PM	(Humbert et al. 2011); (Humbert et al. 2009)	Intake fraction	Yes	ILCD	2000	2.76E+00	kg-PM2.5eq/person
Ionizing radiation, human health	IR	(Frischknecht et al. 2001)	Human exposure efficiency relative to U^{235}	Yes	ILCD	2000	1.33E+03	kBq U-235 air-eq/person
Photochemical ozone formation, impacts on human health	POFP	ReCiPe (Goedkoop et al. 2008)	Tropospheric ozone concentration increase	Yes	ILCD	2000	5.67E+01	kg-NMVOCeq/person
Terrestrial acidification	TA	Accumulated Exceedance (Seppälä et al. 2006)	Accumulated Exceedance (AE)	Yes	ILCD	2000	4.96E+01	AE/person
Terrestrial eutrophication	TE	Accumulated Exceedance (Seppälä et al. 2006)	Accumulated Exceedance (AE)	Yes	ILCD	2000	1.15E+02	AE/person
Freshwater eutrophication	FE	EUTREND model as implemented in ReCiPe (Goedkoop et al. 2008)	Fraction of nutrients reaching freshwater end compartment (P) or marine end compartment (N)	Yes	ILCD	2000	6.20E-01	kg P-eq/person
Marine eutrophication	ME	EUTREND model as implemented in ReCiPe (Goedkoop et al. 2008)	Fraction of nutrients reaching freshwater end compartment (P) or marine end compartment (N)	Yes	ILCD	2000	9.38E+00	kg N-eq/person
Freshwater ecotoxicity	ET	USEtox model (Rosenbaum et al. 2008)	Comparative Toxic Unit for ecosystems (CTUe)	Yes	ILCD	2010	6.65E+02	PAF.m3.d/person
Fossils depletion	RDfos	CML v.4.2 (2013)	Scarcity-based	Yes	ILCD	2000	6.24E+04	MJ/person
Metals/minerals depletion	RD	CML v.4.2 (2013)	Scarcity-based	Yes	ILCD	2000	3.43E-02	kg-Sbeq/person

Table S2. Waste generation data. The amounts are given as percentage of the reference flow of 1000 kg

Material fraction	**%**
Vegetable food waste	26.36
Animal food waste	8.1
Magazines	1.97
Newsprints	7.18
Advertisements	6.95
Books, phone books	0.46
Office paper	1.57
Other clean paper	4.39
Paper and carton containers	4.2
Other clean cardboard	0.87
Milk cartons (carton/plastic)	1.44
Juice cartons (carton/plastic/aluminium)	0.42
Kitchen towels	2.35
Dirty paper	2.53
Dirty cardboard	1.08
Soft plastic	0.1
Plastic bottles	3.26
Hard plastic	1.24
Non-recyclable plastic	0.7
Yard waste, flowers	3.35
Animal excrements and bedding (straw)	0.77
Diapers, sanitary towels, tampons	4.52
Cotton, bandages	0.1
Disposable sanitary products (cloths, gloves)	0.18
Wood	0.33
Textiles	1.72
Shoes, leather	0.4
Rubber	0.05
Plastic products (toys, hangers, pens)	0.32
Cigarette butts	0.18
Other combustibles	0.79
Vacuum cleaner bags	0.82
Clear glass	1.74
Green glass	1.74
Brown glass	1.74
Non-recyclable glass	0.27
Beverage cans (aluminium)	0.32
Aluminium foil and containers	0.4
Food cans (tinplate/steel)	0.7
Plastic-coated aluminium foil	0.78
Other metals	0.5
Soil	0.32
Stones, concrete	0.73
Ash	0.27
Ceramics	0.51
Cat litter	1.1
Batteries	0.15
Other non-combustibles	0.34

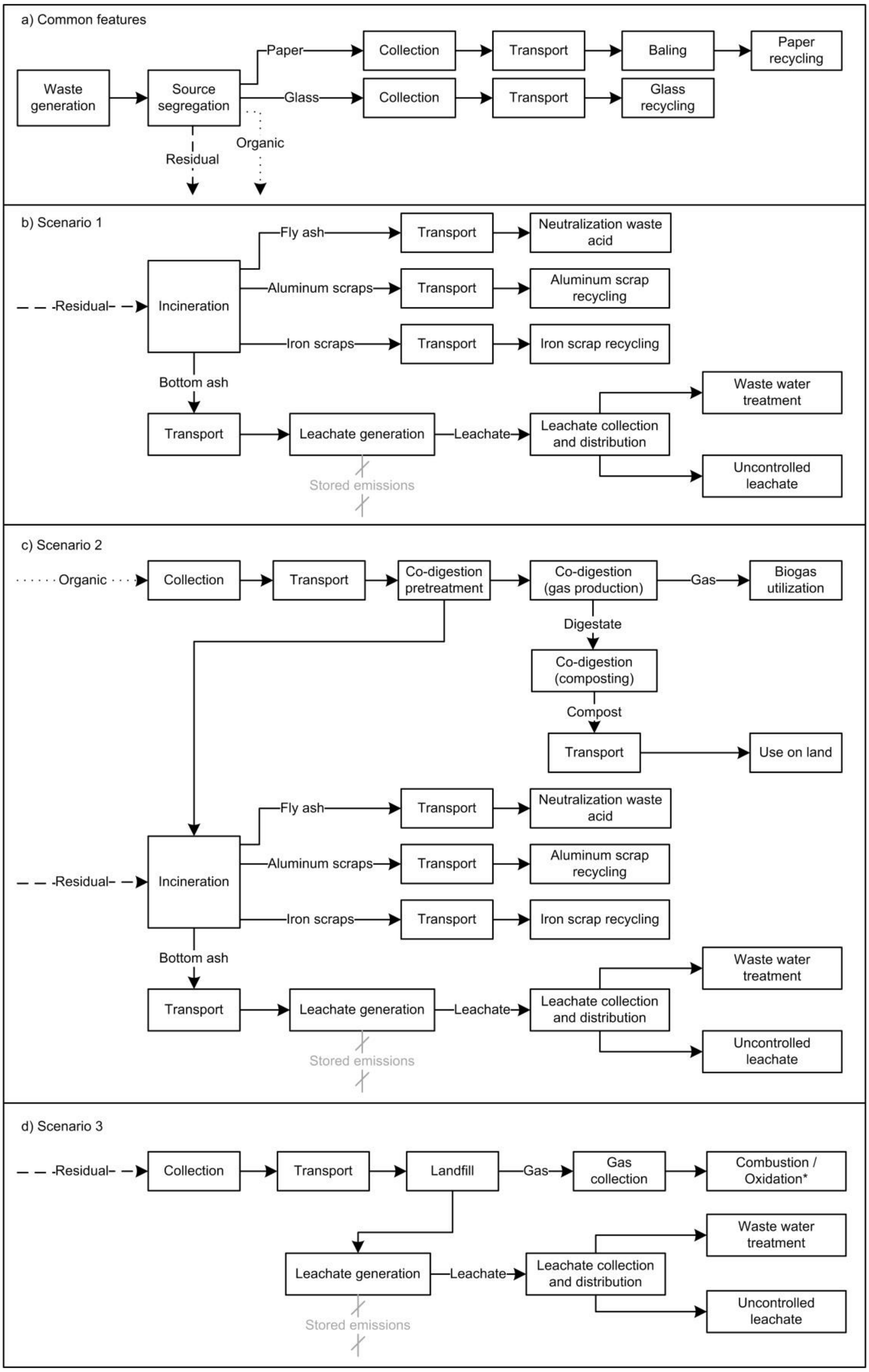


Figure S1. Waste management scenarios tested in the LCA model

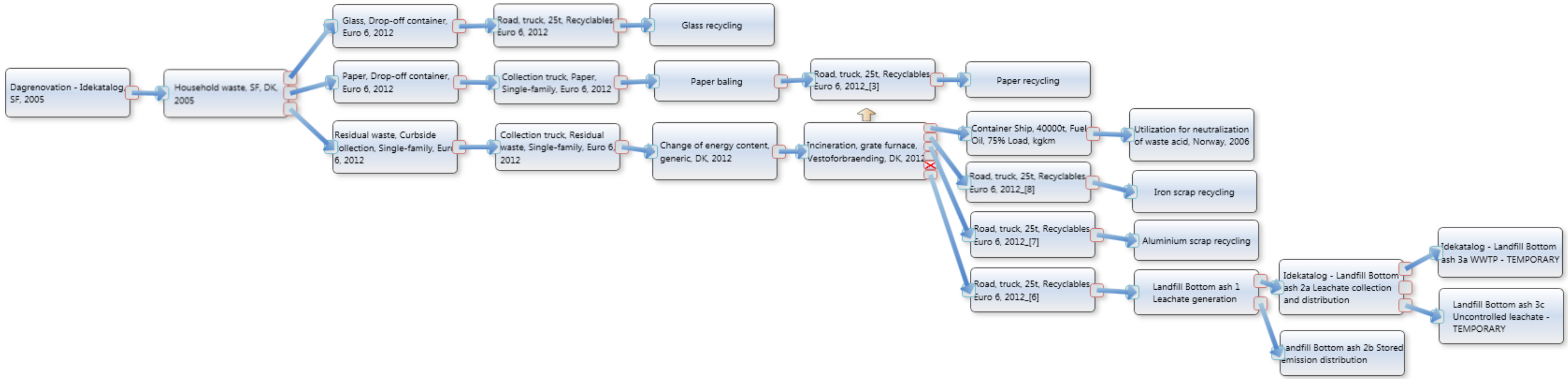


Figure S2. Scenario 1, flow diagram from EASETECH

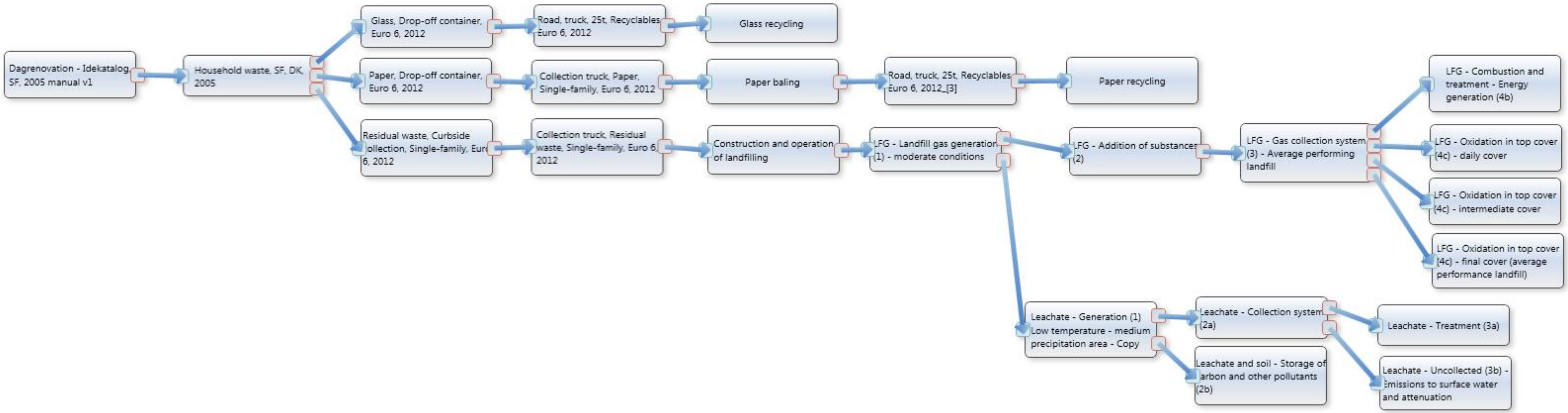


Figure S3. Scenario 3, flow diagram from EASETECH

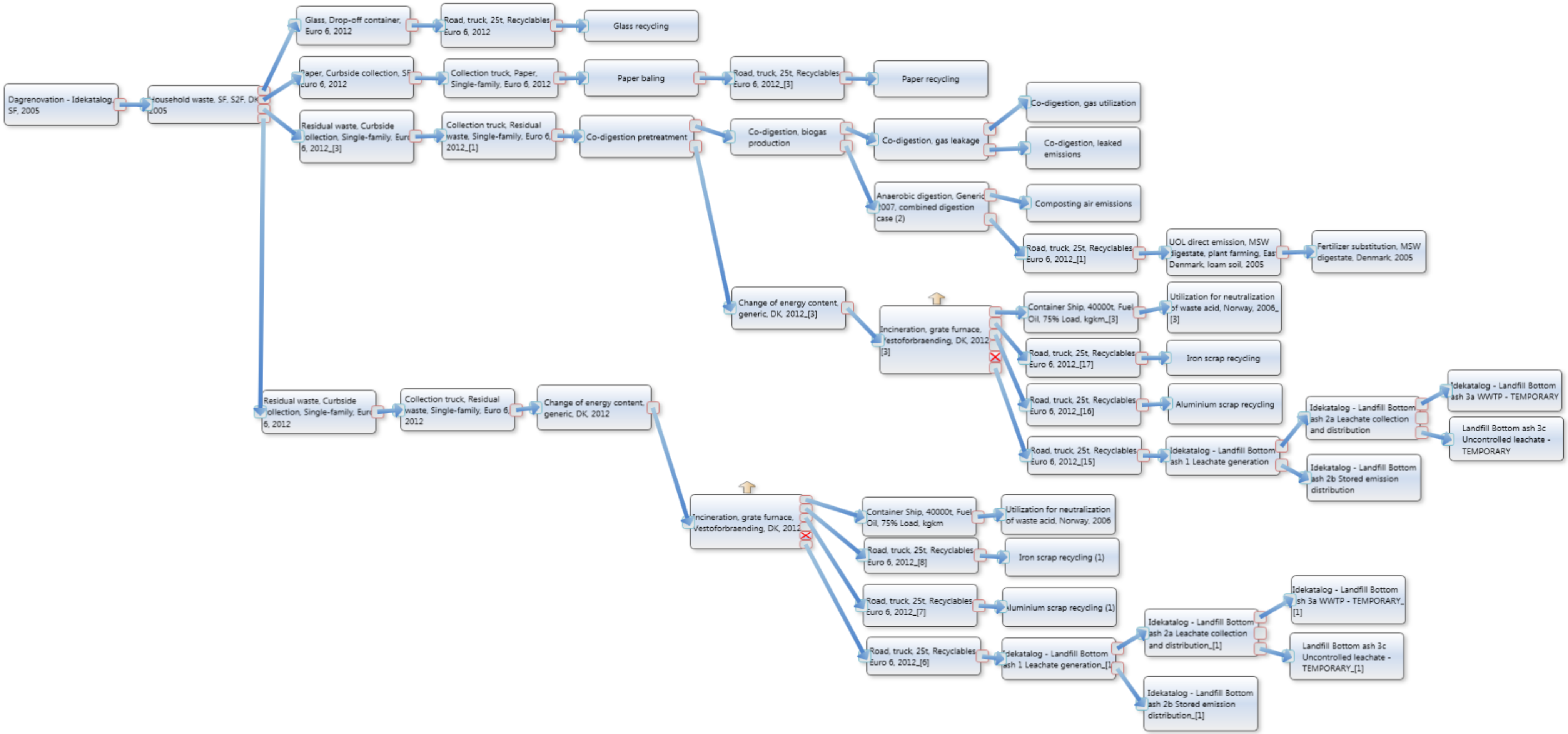


Figure S4. Scenario 2, flow diagram from EASETECH

Table S3. Source segregation matrix for scenario 1 and 3. The “default” fraction comprises all the unspecified material fractions. Values are given as percentage

Fraction name	Glass (%)	Paper (%)	Residues (%)
Other clean paper	0	58	42
Office paper	0	58	42
Books, phone books	0	58	42
Advertisements	0	58	42
Magazines	0	58	42
Newsprints	0	58	42
Brown glass	72	0	28
Green glass	72	0	28
Clear glass	72	0	28
Default	0	0	100

Table S4. Source segregation matrix for scenario 2. The “default” fraction comprises all the unspecified material fractions. Values are given as percentage

Fraction name	Glass (%)	Paper (%)	Organic (%)	Residues (%)
Yard waste, flowers	0	0	75	25
Vegetable food waste	0	0	75	25
Kitchen towels	0	0	75	25
Cat litter	0	0	75	25
Animal food waste	0	0	75	25
Animal excrements and bedding (straw)	0	0	75	25
Other clean paper	0	58	3.5	38.5
Office paper	0	58	3.5	38.5
Books, phone books	0	58	3.5	38.5
Advertisements	0	58	3.5	38.5
Magazines	0	58	3.5	38.5
Newsprints	0	58	3.5	38.5
Default	0	0	3.5	96.5
Brown glass	72	0	3.5	24.5
Green glass	72	0	3.5	24.5
Clear glass	72	0	3.5	24.5

Technologies

Collection

Collection is defined in terms of fuel consumption per tonne of wet waste from the first stop on the collection route to the final stop on the collection route (Larsen et al. 2009). Fuel spent on driving from the garage to the start of the collection route, driving from the final stop on the collection route to the unloading point, and driving from that point back to the garage is considered part of transportation. Table S5 reports collection data for the three waste management scenarios according to the subdivision in Figure S1. The technology and the processes are part of the EASETECH library; amounts were entered according to Jensen et al. (2013).

Table S5. Collection processes data

	Name	Technology	Amount	Unit	Per
(a) Common features					
Collection of glass	Glass, Drop-off container, Euro 6, 2012	Collection Vehicle, 10t Euro6, urban traffic, 1 liter diesel, 2012	0.0049	l	kg Total Wet Weight
Collection of paper	Paper, Curbside collection, SF, Euro 6, 2012	Collection Vehicle, 10t Euro6, urban traffic, 1 liter diesel, 2012	0.0049	l	kg Total Wet Weight
(b) Scenario 1					
Collection of residual waste	Residual waste, Curbside collection, Single-family, Euro 6, 2012	Collection Vehicle, 10t Euro6, urban traffic, 1 liter diesel, 2012	0.00327	l	kg Total Wet Weight
(c) Scenario 2					
Collection of organic waste	Residual waste, Drop-off container, Single-family, Euro 6, 2012	Collection Vehicle, 10t Euro6, urban traffic, 1 liter diesel, 2012	0.00327	l	kg Total Wet Weight
(d) Scenario 3					
Collection of residual waste	Residual waste, Curbside collection, Single-family, Euro 6, 2012	Collection Vehicle, 10t Euro6, urban traffic, 1 litre diesel, 2012	0.00327	l	kg Total Wet Weight

Transport

The transport carried out by collection truck is based on the Danish study by Larsen et al. (2009) mentioned in the previous section. The transportation by road truck is defined in terms of fuel consumption per kg of wet waste per km and does not include empty return transport. The process is taken from the EASETECH library and is based on a report from the Danish Ministry of Transport (Transportministeriet 2010). Transportation by container ship is based on an EDIP process implemented in EASEWASTE (Kirkeby et al. 2006) and imported in EASETECH. Fuel consumption is given in kg per km of transport. Transport processes data is reported in Table S6.

Glass recycling

Glass recycling is modelled as in Jensen et al. (2013). The recycled glass is set to avoid primary production of packaging glass with a recovery rate of 89%.

Paper recycling

Paper is recycled to newsprints after an intermediate stage where it is baled. Both datasets are taken from Jensen et al. (2013) and are compliant to the study of Brogaard et al. (2014). Paper is recovered with an efficiency of 84%.

Incineration

The incineration process is taken from the EASETECH library and describes a generic Danish incineration plant in 2012. The flue gas cleaning system is based on Vestforbrænding in 2011. The process describes a grate incineration with wet flue gas cleaning. NOx is removed with SNCR and Dioxin and Hg is removed with activated carbon. The outputs of the process are fly ash, iron scraps, aluminium scraps, waste water and cleaned flue gas.

Table S6. Transport processes data

	Name	Technology	km driven	Amount	Unit	Per
(a) Common features						
Transport of glass	Road, truck, 25t, Recyclables, Euro 6, 2012	Transport vehicle, 25t Euro6, 1 liter diesel, 2012	200	0.00002	l	kg Total Wet Weight * km driven
Transport of paper (1)	Collection truck, Paper, Single-family, Euro 6, 2012	Collection Vehicle, 10t Euro6, urban traffic, 1 liter diesel, 2012	30	0.00013	l	kg Total Wet Weight * km driven
Transport of paper (2)	Road, truck, 25t, Recyclables, Euro 6, 2012	Transport vehicle, 25t Euro6, 1 liter diesel, 2012	365	0.00002	l	kg Total Wet Weight * km driven
(b) Scenario 1						
Transport of residual waste	Collection truck, Residual waste, Single-family, Euro 6, 2012	Collection Vehicle, 10t Euro6, urban traffic, 1 liter diesel, 2012	30	0.00002	l	kg Total Wet Weight * km driven
Transport of fly ash	Container Ship	Container Ship, 40000t, Fuel Oil, 75% Load, kgkm	500	1	kg	kg Total Wet Weight * km driven
Transport of iron scrap	Road, truck, 25t, Recyclables, Euro 6, 2012	Transport vehicle, 25t Euro6, 1 liter diesel, 2012	500	0.00002	l	kg Total Wet Weight * km driven
Transport of aluminium scrap	Road, truck, 25t, Recyclables, Euro 6, 2012	Transport vehicle, 25t Euro6, 1 liter diesel, 2012	400	0.00002	l	kg Total Wet Weight * km driven
Transport of bottom ash	Road, truck, 25t, Recyclables, Euro 6, 2012	Transport vehicle, 25t Euro6, 1 liter diesel, 2012	500	0.00002	l	kg Total Wet Weight * km driven
(c) Scenario 2						
Transport of organic waste	Collection truck, Residual waste, Single-family, Euro 6, 2012	Collection Vehicle, 10t Euro6, urban traffic, 1 liter diesel, 2012	30	0.00009	l	kg Total Wet Weight * km driven
Transport of fly ash	Container Ship	Container Ship, 40000t, Fuel Oil, 75% Load, kgkm	500	1	kg	kg Total Wet Weight * km driven
Transport of iron scrap	Road, truck, 25t, Recyclables, Euro 6, 2012	Transport vehicle, 25t Euro6, 1 liter diesel, 2012	500	0.00002	l	kg Total Wet Weight * km driven
Transport of aluminium scrap	Road, truck, 25t, Recyclables, Euro 6, 2012	Transport vehicle, 25t Euro6, 1 liter diesel, 2012	400	0.00002	l	kg Total Wet Weight * km driven
Transport of bottom ash	Road, truck, 25t, Recyclables, Euro 6, 2012	Transport vehicle, 25t Euro6, 1 liter diesel, 2012	500	0.00002	l	kg Total Wet Weight * km driven
Transport of compost	Road, truck, 25t, Recyclables, Euro 6, 2012	Transport vehicle, 25t Euro6, 1 liter diesel, 2012	200	0.00002	l	kg Total Wet Weight * km driven
(d) Scenario 3						
Transport of residual waste	Collection truck, Residual waste, Single-family, Euro 6, 2012	Collection Vehicle, 10t Euro6, urban traffic, 1 liter diesel, 2012	30	0.00009	l	kg Total Wet Weight * km driven

The energy substitution represents a simple system with the incinerator connected to the district heating net of a centralized CHP-plant. Electricity recovery has an efficiency of 22%, heat is recovered for the 73%. Data complies to Vesforbrænding green accounting (Vestforbrænding 2012).

Fly ash

The process models the utilization of APC residues for neutralization of waste acid in Langøya, Norway substituting limestone (0.035%). The dataset corresponds to the one utilized in Jensen et al. (2013); data originate from a study performed by ISWA, WGTT (Working Group on Thermal Treatment of Waste) providing a systematic overview of alternatives for management of APC residues (Astrup 2008).

Iron scraps

The process models shredding and reprocessing of steel scrap in Sweden, in 2007. Incoming steel scarp is shredded, melted and casted for further production of packages and other metal products with an efficiency of 87%. Emissions to air are cleaned with use of textile filters. The dataset is the same as the one utilized in Jensen et al. (2013).

Aluminium scraps

Aluminium scrap is remelted to aluminium sheets with an efficiency of 94%. The process is described in Jensen et al. (2013). All data on emissions, energy use and resource use is based on Stena Aluminium (2007).

Bottom ash landfill

As in Jensen et al. (2013), half of the bottom ash is recovered in road construction, while the remaining is landfilled in a mineral waste landfill. The substitution of gravel that would otherwise be needed for road construction is modelled with extraction and crushing of gravel from Ecoinvent v2 (Frischknecht et al. 2007). The mineral landfill is modelled as described in Jensen et al. (2013), with the leaching profile as described in Table S7.

Anaerobic digestion: pre-treatment, biogas production and utilization

The anaerobic digestion process in Jensen et al. (2013) is based on the Swedish plant of Karpalund, also present in the EASETECH library. The process describes biogas production from organic waste, including biogas utilization. The organic waste stream undergoes a pre-treatment, with transfer coefficients as in Table S8. Process is mesophilic (38 degrees C) with heat exchange. Use of thermal energy has been assumed to 7.9% of energy content in produced biogas by the production plant, while the use of electrical energy has been assumed to 3.6% of energy content in produced biogas in the production plant. Biogas is utilized 70 % for heat production, 30 % as vehicle fuel. A leakage of 5 % was assumed, and the respective emissions to the environment were taken into account.

Composting

Digestate from anaerobic digestion is composted before being applied on land. The aerobic degradation unit and its air emissions are taken from the EASETECH library and are based on Davidsson et al. (2007) and Pipatti et al. (2006). VS, biogenic C and N are degraded during aerobic digestion as in Table S9. Emissions to the environment are described in the following Table S10.

Table S7. Leaching profile for the bottom ash landfill. Leachate concentrations in mg/l

Name	Time period 1	Time period 2	Time period 3	Time period 4
Duration (yrs)	20	20	30	30
DOC	57.31	105.9	117.2	151.3
Sb	0.0205	0.0443	0.0467	0.0672
Cl	3062.8	5340.6	4271	4791.4
Zn	0.0075	0.0075	0.0504	0.1154
V	0.0087	0.0187	0.0196	0.0281
Ti	2.50E-05	0.0001	0.0001	0.0001
Sr	1.695	2.257	1.813	2.178
Sn	0.002	0.0048	0.0052	0.0076
Se	0.066	0.0892	0.1284	0.1789
S	2701	3162	2259	2440
Pb	0.0107	0.0158	0.0137	0.0176
P	0.4231	0.485	0.4985	0.6268
Ni	0.0014	0.0041	0.0037	0.0044
Na	1134	3351	2992	3547
Mo	0.6178	1.2606	1.2983	1.6336
Mn	0.0011	0.0027	0.0036	0.005
Mg	0.5103	1.0033	1.4817	2.0771
K	270.3	468.36	561.4	743.9
Fe	3.50E-05	0.0003	0.0005	0.0012
Cu	0.9343	1.8565	2.0053	2.5675
Cr	0.0913	0.1524	0.21	0.2894
Co	0.0001	0.0003	0.0004	0.0006
Cd	0.0001	0.0002	0.0002	0.0003
Ca	961.22	1153	844.7	935.9
Be	0.0003	0.001	0.0011	0.0017
Ba	0.0181	0.0486	0.055	0.082
As	0.0113	0.0147	0.0116	0.0137
Al	28.88	62.08	65.2	93.43

Table S8. Transfer coefficient for the pretreatment of organic waste sent to anaerobic digestion

Fraction name	Anaerobic digestion (%)	Residues (%)
Yard waste, flowers	75	25
Vegetable food waste	75	25
Kitchen towels	75	25
Cat litter	75	25
Animal food waste	75	25
Animal excrements and bedding (straw)	75	25
Default	0	100

Table S9. Degradation during composting phase

Transfer coefficient for	Degraded (%)	Compost (%)
VS	13.5	86.5
C bio	13.5	86.5
N	67	33

Table S10. Emissions to the environment, composting process

Material property	Transformed at (%) into	Elementary exchange	Compartment	Sub compartment	With the conversion factor
kg C bio	96.1	Carbon dioxide, non-fossil	air	unspecified	44/12
kg C bio	3.9	Methane, non-fossil	air	unspecified	16/12
kg N	3.23	nitrogen	air	unspecified	28/14
kg N	94.08	Ammonia	air	unspecified	17/13
kg N	0.77	Dinitrogen monoxide	air	unspecified	44/14

Use on land and fertilizer substitution

The composted digestate is applied for plant farming on loam soil, as in Jensen et al. (2013). The agricultural profile describes the emissions to air, surface water, groundwater and soil accumulation from land application of composted digestate for substitution of inorganic fertilizer. Fuel use of a diesel powered manure spreader for land application of digesate was assumed. The fate of carbon (C) and nitrogen (N) is simulated with DAISY, one dimensional, deterministic agro-ecosystem model. The model couples hydrological model, crop growth model, mineral nitrogen, and soil organic matter model. The digestate substitutes average P and K fertilizers with an efficiency of 100%, while average N fertilizer is substituted with an efficiency of 40% (Hansen et al. 2006). Introduction of heavy metal to the agricultural soil was estimated based on the heavy metal content of N, P, K fertilizer provided by Audsley et al. (1997)

Landfill

The landfill processes utilized in scenario 3 refer to a moderate condition landfill and are taken from the EASETECH library and comprise construction and operation, as well as landfill gas and leachate processes. The default processes established in EASETECH are documented in an internal report (DTU 2014). The calculation structure is described in Clavreul et al. (2014).

SI.2 LCA results and sensitivity

Figure S5 shows the normalized impact scores for all scenarios and impact categories. The impact categories with the highest overall scores as PE are climate change (GWP), human toxicity with non-carcinogenic effects (HTnc), marine eutrophication (ME), freshwater ecotoxicity (ET) and depletion of abiotic resources (RDfos).

Regarding GWP, scenario 1 and 2 show the highest benefits compared to scenario 3. Scenario 1 has the largest benefits (-0.09 PE) because a substantial portion of the waste is routed to the incinerator, where electricity and heat are recovered and contribute in displacing electricity production from coal. Scenario 2 shows less overall benefits (-0.08 PE) for the lower efficiency of the energy recovery of the anaerobic digester, and for the reduced waste flow to this treatment scenario. The minimal difference between the two scenarios comes from the fact that the residuals are ultimately routed to an incinerator with the same characteristics as the one in scenario 1. As far as scenario 3 is concerned (-0.02 PE), the savings arise from the recycling aspect, whereas the treatment option leads to impacts related to methane emissions from the landfilled waste. The impacts related to transport are of the same order of magnitude and negligible for all the waste management scenarios. For HTnc, impacts are remarkable mainly for scenario 2 (0.21 PE), due to the zinc process specific emissions arising from the use on land of the compost. The major impacts for ME are connected with the landfill management scenario (0.3 PE), where nitrate and ammonium ion leach to surface water. ET shows the highest scores for scenario 1 (-0.05 PE) and 2 (0.17 PE), but with opposite sign. For scenario 1, savings are related to the paper avoided production. In scenario 2, the same recycling of paper occurs, but the burden is shifted by the use on land of the compost. Finally, both in scenario 1 (-0.08 PE) and 2 (-0.06 PE) there is a total overall saving of RDfos thanks for the substitution of fossil fuels by the energy recovery.

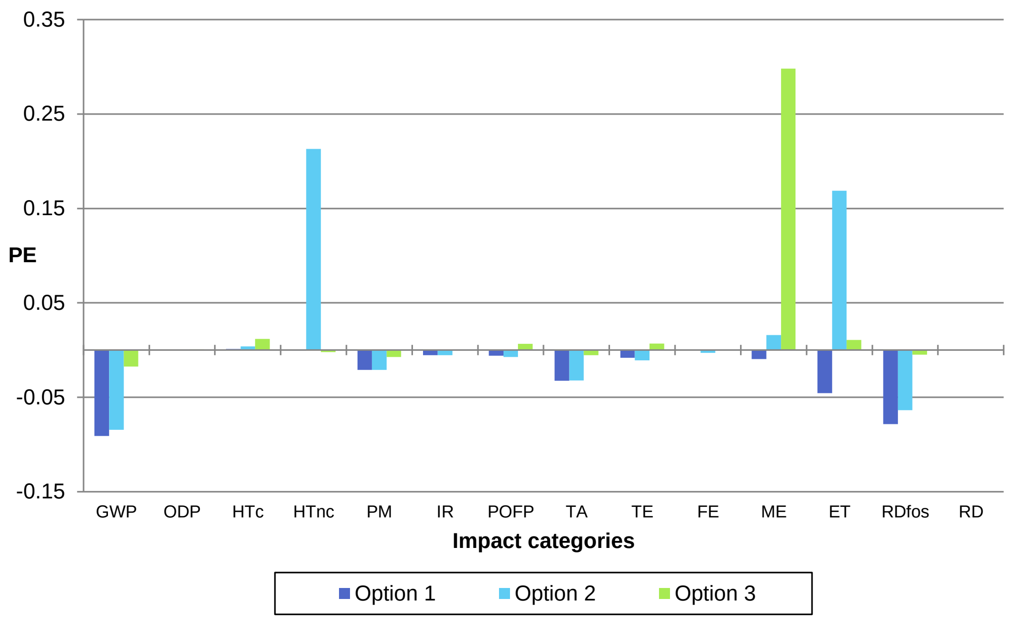


Figure S5. Normalized result scores of the LCA case study. Results are given in Persons Equivalents (PE). The impact categories are: climate change (GWP), stratospheric ozone depletion (ODP), human toxicity, cancer effects (HTc), human toxicity, non-cancer effects (HTnc), particulate matter (PM), ionizing radiation (IR), photochemical ozone formation (POFP), terrestrial acidification (TA), terrestrial eutrophication (TE), freshwater eutrophication (FE), marine eutrophication (ME), freshwater ecotoxicity (ET), fossils depletion (RDfos), metals/minerals depletion (RD)

Figures S6 – S7 illustrate the processes´ contribution to the impacts. The contribution analysis is subdivided in three figures to arrange the impacts according to their order of magnitude. The detailed list of processes and substances contributing the most to the impacts is reported in Table S11. Within these, a total of 80 parameters for each scenario were selected, including aspects such as waste characteristics (input specific features), process specific features of the management options, fuel consumption, distances driven, recycling and substitution rates. The amount of the most abundant waste fractions was also parameterized, maintaining the same functional unit. The three waste management solutions happen to have some shared processes and parameters, but common parameters between compared scenarios are not requested for the methodological approach proposed in this paper. A complete list of the parameters is available in Table S12.

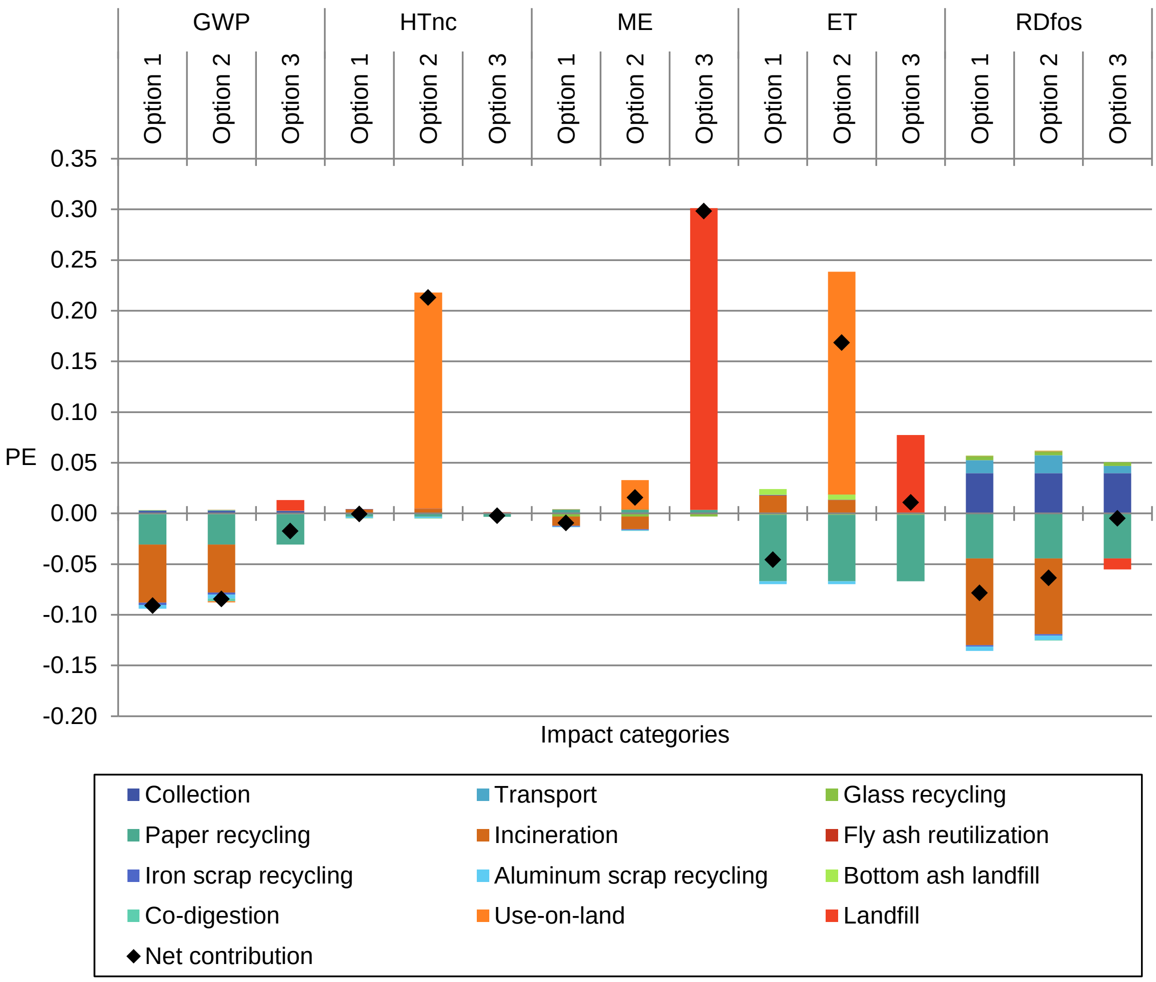
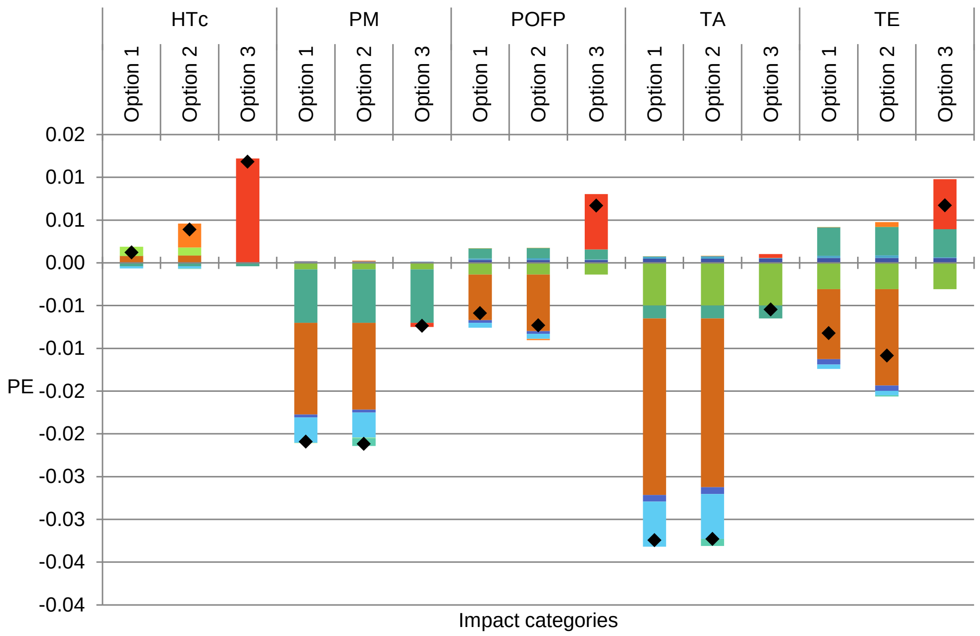


Figure S6 Contribution analysis for GWP, HTnc, ME, ET, RDfos. The black diamonds indicate the position of the net result score

(a)



(b)

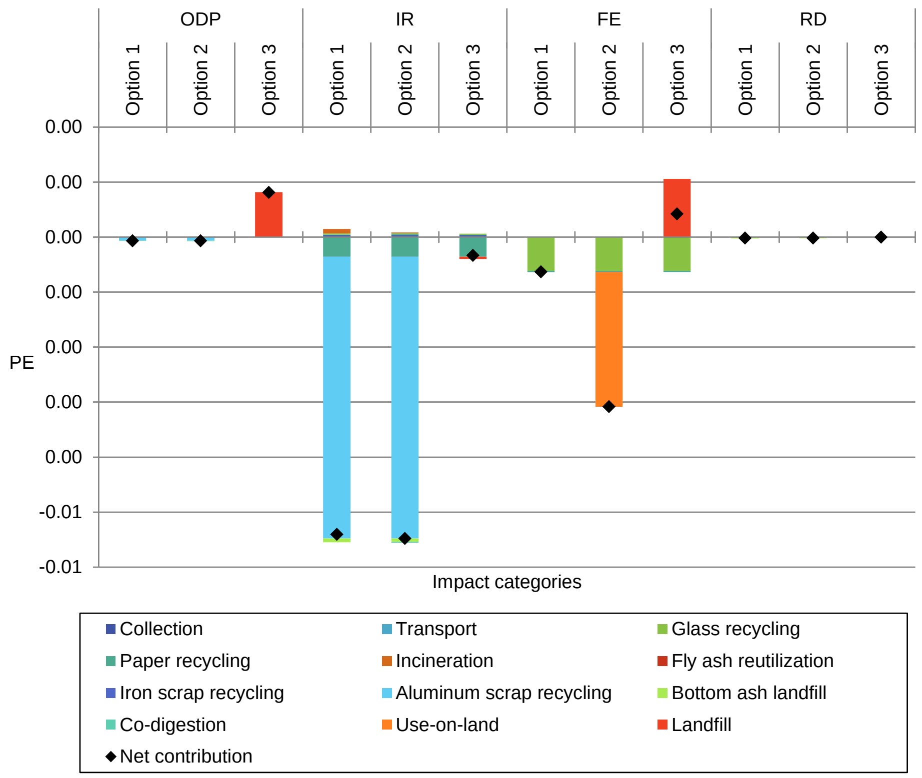


Figure S7 Contribution analysis for HTc, PM, POFP, TA, TE (a) and for ODP, IR, FE, RD (b). The black diamonds indicate the position of the net result score

Table S11 Contribution analysis for each impact category and each case study scenario

Global warming potential (GWP)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-9.09E-02**		**-8.45E-02**		**-1.76E-02**	
	Process	**Substance**	**Process**	**Substance**	**Process**	**Substance**
Impacts	Transport	CO2 fossil, process specific emission	Transport	CO2 fossil, process specific emission	Oxidation in top cover	Methane, non-fossil, input specific
	Paper baling	CO2 fossil, electricity (process specific emission)	Paper baling	CO2 fossil, electricity (process specific emission)	Leachate treatment	CO2 fossil, electricity (process specific emission)
			Co-digestion pre-treatment	CO2 fossil, electricity (process specific emission)	Transport	CO2 fossil, process specific emission
Benefits	Paper recycling	CO2 fossil, electricity (process specific emission)	Paper recycling	CO2 fossil, electricity (process specific emission)	Paper recycling	CO2 fossil, electricity (process specific emission)
	Incineration	CO2 fossil, electricity (process specific emission)	Incineration	CO2 fossil, electricity (process specific emission)	Energy generation LFG	CO2 fossil, electricity (process specific emission)
		CO2 fossil, heat (process specific emission)		CO2 fossil, heat (process specific emission)		CO2 fossil, heat (process specific emission)
			Gas utilization	CO2 fossil, electricity (process specific emission)	Storage of carbon	CO2 fossil storage (the residual C bio from anaerobic digestion is stored in the landfill - benefit - and considered as CO2 fossil)
				CO2 fossil, heat (process specific emission)		
	Aluminium recycling	Al primary production (CO2 fossil from electricity consumption, background system)	Aluminium recycling	Al primary production (CO2 fossil from electricity consumption, background system)		
	Iron recycling	Steel primary production (CO2 fossil from electricity consumption, background system)	Iron recycling	Steel primary production (CO2 fossil from electricity consumption, background system)		

Stratospheric ozone depletion (ODP)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-6.58E-05**		**-6.68E-05**		**8.14E-04**	
	Process	Substance	Process	Substance	Process	Substance
Impacts	Transport	CFC 11, diesel			Oxidation in top cover	Ethane from input specific emissions
	Glass recycling	CFC 11, light fuel oil				
	Incineration	CFC 11, process water and activated carbon procurement process specific emissions				
Benefits	Aluminium recycling	CFC 11, electricity mix used for primary Al production	Aluminium recycling	CFC 11, electricity mix used for primary Al production	LFG energy generation	CFC 11 electricity (process specific emissions)
	Paper recycling	CFC11 process specific emissions for procurement of spruce wood and related to marginal electricity requirements (hard coal)	Paper recycling	CFC11 process specific emissions for procurement of spruce wood and related to marginal electricity requirements (hard coal)		
	BA leachate generation	Halon avoided for avoided gravel crushing at mine				

Table S11. (continued) Contribution analysis for each impact category and each case study scenario

Human toxicity carcinogenic (HTc)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**1.21E-03**		**3.88E-03**		**1.18E-02**	
	Process	Substance	Process	Substance	Process	Substance
Impacts	Uncollected leachate	Chromium to soil and water from input-specific emissions	Uncollected leachate	Chromium to soil and water from input-specific emissions	Leachate treatment	Chromium, input-specific emissions
	WWTP	Chromium, input-specific emissions	WWTP	Chromium, input-specific emissions		
	Incineration	Mercury, input specific emissions	Incineration	Mercury, input specific emissions		
			UOL	Chromium, nickel and lead from input-specific emissions		
Benefits	Paper recycling	Mercury from process-specific emissions of primary production of paper	Paper recycling	Mercury from process-specific emissions of primary production of paper	LFG energy generation	Mercury avoided from electricity generation
	Aluminium recycling	Mercury from process-specific emissions of primary production of aluminium	Aluminium recycling	Mercury from process-specific emissions of primary production of aluminium	Paper recycling	Mercury from process-specific emissions of primary production of paper
	Leachate generation	Chromium avoided for avoided gravel crushing at mine	Leachate generation	Chromium avoided for avoided gravel crushing at mine		
			Fertilizer substitution	Cadmium emission avoided from fertilizer substitution		

Human toxicity non carcinogenic (HTnc)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-7.37E-04**		**2.13E-01**		**-2.24E-03**	
	Process	Substance	Process	Substance	Process	Substance
Impacts	Incineration	Mercury, input specific emissions	UOL	Zinc from input-specific emissions	Leachate treatment	Zinc, input specific emission
Benefits	Paper recycling	Mercury from process-specific emissions of primary production of paper	Fertilizer substitution	Zinc emission avoided from fertilizer substitution	Paper recycling	Mercury from process-specific emissions of primary production of paper
	Aluminum recycling	Mercury from process-specific emissions of primary production of aluminum			LFG energy generation	Mercury avoided from electricity generation

Particulate matter (PM)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-2.09E-02**		**-2.12E-02**		**-7.36E-03**	
	Process	Substance	Process	Substance	Process	Substance
Impacts					Leachate treatment	Particulates, electricity
Benefits	Paper recycling	Particulates from the electricity requirements for primary paper production	Paper recycling	Particulates from the electricity requirements for primary paper production	Paper recycling	Particulates from the electricity requirements for primary paper production
	Incineration	Particulates, electricity process specific emissions	Aluminium recycling	Particulates and sulphur dioxide, electricity process specific emissions for primary Aluminium production	LFG energy generation	Sulphur dioxide and particulates from electricity and heat process specific emissions
		Particulates, heat process specific emissions	Incineration	Particulates, electricity process specific emissions	Glass recycling	Sulphur dioxide avoided process specific emissions from glass primary production
	Aluminium recycling	Particulates and sulphur dioxide, electricity process specific emissions for primary Aluminium production		Particulates, heat process specific emissions		
			Gas utilization	Particulates and sulphur dioxide, electricity process specific		

Table S11. (continued) Contribution analysis for each impact category and each case study scenario

Ionising radiation (IR)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-5.41E-03**		**-5.48E-03**		**-3.34E-04**	
	Process	Substance	Process	Substance	Process	Substance
Impacts					Leachate treatment	C-14, electricity process specific
					Paper baling	C-14, electricity process specific
Benefits	Paper recycling	C-14, paper primary production, electricity process	Paper recycling	C-14, paper primary production, electricity process	Paper recycling	C-14, paper primary production, electricity process
	Aluminium recycling	C-14, Aluminium primary production, electricity process	Aluminium recycling	C-14, Aluminium primary production, electricity process	LFG energy generation	C-14, electricity process specific
			Leachate generation	C-14, gravel crushed at mine		
Photochemical oxidant formation (POFP)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-5.88E-03**		**-7.31E-03**		**6.68E-03**	
	Process	Substance	Process	Substance	Process	Substance
Impacts	Paper recycling	Nitrogen oxides, process specific emissions	Paper recycling	Nitrogen oxides, process specific emissions	Oxidation in top cover	Methane, non-fossil, input specific emission
			Biogas production	Nitrogen oxides, diesel oil in truck	LFG energy generation	Nitrogen oxides, process specific emissions
					Paper recycling	Nitrogen oxides, process specific emissions
Benefits	Glass recycling	Nitrogen oxides, glass primary production, process specific emissions	Glass recycling	Nitrogen oxides, glass primary production, process specific emissions	Glass recycling	Nitrogen oxides, glass primary production, process specific emissions
	Incineration	Nitrogen oxides avoided, district heating	Gas utilization	Nitrogen oxides, electricity process specific		
	Aluminium recycling	Sulphur dioxide, nitrogen oxides, Aluminium primary production, process specific	Incineration	Nitrogen oxides avoided, district heating		
	Iron recycling	Nitrogen oxides, steel sheets production, process-specific				
Terrestrial acidifcation (TA)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-3.24E-02**		**-3.23E-02**		**-5.45E-03**	
	Process	Substance	Process	Substance	Process	Substance
Benefits	Glass recycling	Sulphur dioxide, nitrogen oxides, glass primary production	Fertilizer substitution	sulphur dioxide, ammonia, nitrogen oxides, average fertilizers process-specific emissions	Glass recycling	Sulphur dioxide, nitrogen oxides, glass primary production
	Incineration	Sulphur dioxide, nitrogen oxides, district heating	Gas utilization	Sulphur dioxide, nitrogen oxides, electricity and heat	Paper recycling	sulphur dioxide, paper primary production
	Paper recycling	Sulphur dioxide, paper primary production	Glass recycling	Sulphur dioxide, nitrogen oxides, glass primary production	LFG energy generation	sulphur dioxide, electricity and heat
	Aluminium recycling	sulphur dioxide, aluminium primary production (electricity mix and process-specific emissions)	Paper recycling	sulphur dioxide, paper primary production		
	Iron recycling	sulphur dioxide, nitrogen oxides, steel sheets primary production, hard coal and process-specific	Iron recycling	sulphur dioxide, nitrogen oxides, steel sheets primary production, hard coal and process-specific		
			Aluminium recycling	sulphur dioxide, aluminium primary production (electricity mix and process-specific emissions)		

Table S11. (continued) Contribution analysis for each impact category and each case study scenario

Terrestrial eutrophication (TE)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-8.22E-03**		**-1.09E-02**		**6.72E-03**	
	Process	Substance	Process	Substance	Process	Substance
Impacts	Paper recycling	Nitrogen oxides, process specific emissions	UOL Biogas production	Ammonia, input-specific emissions Nitrogen oxides, electricity and gas utilization	Paper recycling LFG energy generation	Nitrogen oxides, process specific emissions Nitrogen oxides, process specific emissions
Benefits	Glass recycling Incineration Aluminium recycling Iron recycling	Nitrogen oxides, ammonia, glass primary production Nitrogen oxides, ammonia, glass primary production, heat and electricity Nitrogen oxides, Aluminium primary production Nitrogen oxides, steel sheets primary production	Fertilizer substitution Gas utilization Incineration Aluminium recycling Iron recycling Glass recycling	Nitrogen oxides, ammonia, average fertilizer substitution Nitrogen oxides, electricity and heat process-specific emissions Nitrogen oxides, ammonia, glass primary production, heat and electricity Nitrogen oxides, Aluminium primary production Nitrogen oxides, steel sheets primary production Nitrogen oxides, ammonia, glass primary production	Glass recycling	Nitrogen oxides, ammonia, glass primary production
Freshwater eutrophication (FE)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-6.33E-04**		**-3.08E-03**		**4.22E-04**	
	Process	Substance	Process	Substance	Process	Substance
Impacts					Leachate treatment	Phosphate, input specific emissions
Benefits	Glass recycling Paper recycling	Phosphate, glass primary production, process-specific Phosphorous, paper primary production, process-specific	Fertilizer substitution Glass recycling	Phosphorous, average P fertilizer Phosphate, glass primary production, process-specific	Glass recycling	Phosphate, glass primary production, process-specific
Marine eutrophication (ME)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-9.58E-03**		**1.58E-02**		**2.98E-01**	
	Process	Substance	Process	Substance	Process	Substance
Impacts	Paper recycling	Nitrogen oxides, process-specific emissions	UOL Biogas production Paper recycling	Nitrate, input specific emissions Nitrogen oxides, diesel oil, electricity, heat Nitrogen oxides, process-specific emissions	Leachate treatment	Nitrate, ammonium ion, input-specific emissions
Benefits	Incineration Glass recycling aluminium recycling Iron recycling	Nitrogen oxides, heat and electricity Nitrogen oxides, glass primary production Nitrogen oxides, aluminium primary production Nitrogen oxides, steel sheets primary production	Incineration Gas utilization Glass recycling aluminium recycling Iron recycling	Nitrogen oxides, heat and electricity Nitrogen oxides, heat and electricity Nitrogen oxides, glass primary production Nitrogen oxides, aluminium primary production Nitrogen oxides, steel sheets primary production		

Table S11. (continued) Contribution analysis for each impact category and each case study scenario

Freshwater ecotoxicity (ET)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-4.58E-02**		**1.69E-01**		**1.07E-02**	
	Process	Substance	Process	Substance	Process	Substance
Impacts	Uncontrolled leachate WWTP	Copper and copper ion, input-specific emissions Copper ion, chromium, input-specific emissions	UOL	Zinc, copper, nickel, chromium, input-specific emissions	Leachate treatment	Zinc ion, chromium, phenol, input-specific emissions
Benefits	Paper recycling aluminium recycling	Zinc ion, Copper ion, paper primary production Vanadium, zinc, nickel, aluminium primary production	Paper recycling aluminium recycling Fertilizer substitution	Zinc ion, Copper ion, paper primary production Vanadium, zinc, nickel, aluminium primary production Zinc, copper, chromium, average fertilizer process-specific	Paper recycling	Zinc ion, Copper ion, paper primary production

Resources depletion, fossil (RDfos)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-7.85E-02**		**-6.36E-02**		**-4.84E-03**	
	Process	Substance	Process	Substance	Process	Substance
Impacts	Transport	Oil, crude, diesel external process	Transport UOL Leachate generation	Oil, crude, diesel external process Crude oil, farm tractor Coal, brown, natural gas, machines	Transport	Oil, crude, diesel external process
Benefits	Paper recycling Incineration aluminium recycling	Coal, crude oil, paper primary production Coal, crude oil, electricity Coal, brown, coal, hard, aluminium primary production	Paper recycling Incineration aluminium recycling	Coal, crude oil, paper primary production Coal, crude oil, electricity Coal, brown, coal, hard, aluminium primary production	Paper recycling LFG energy generation	Coal, crude oil, paper primary production Coal, crude oil, electricity

Resources depletion (RD)	Scenario 1		Scenario 2		Scenario 3	
Net result (PE)	**-1.90E-05**		**-1.69E-05**		**3.29E-07**	
	Process	Substance	Process	Substance	Process	Substance
Impacts	Incineration	Lead, activated carbon requirement	Incineration	Lead, activated carbon requirement	Construction and operation of landfill	Process-specific emission
Benefits	Leachate generation	Zinc, chromium, gravel avoided	Leachate generation	Zinc, chromium, gravel avoided	LFG energy generation	aluminium, bauxite, electricity

Table S12. Complete list of the parameters used in the case studies

Name	Unit	Process	Specific	Linked to an external process	Scenario 1	Scenario 2	Scenario 3
alu_rec	kg/kg Total Wet Weight	Aluminium recycling	Substitution of primary production	Yes	x	x	
co2_pap	kg/kg Total Wet Weight	Paper recycling	Carbon dioxide, fossil, process-specific	No	x	x	x
coll_glass	l/ton Total Wet Weight	Glass collection	Fuel consumption	Yes	x		x
coll_pap	l/ton Total Wet Weight	Paper collection	Fuel consumption	Yes	x		x
coll_res	l/ton Total Wet Weight	Residual waste collection	Fuel consumption	Yes	x	x	x
cop_inc	kg/kg Total Wet Weight	Incineration	Copper ion, process-specific	No	x	x	
elec_rec	kWh/kWh	Incineration	Recovery of electricity	Yes	x	x	
glass_rec	kg/kg Total Wet Weight	Glass recycling	Substitution of primary production	Yes	x	x	x
glass_seg	%	Source segregation	Percentage of segregated material	No	x	x	x
gravel_rec	kg/kg Total Wet Weight	Bottom ash recycling	Substitution of primary production	Yes	x	x	
heat_rec	kWh/kWh	Incineration	Recovery of heat	Yes	x	x	
lime_rec	kg/kg Total Wet Weight	Utilization for neutralization of waste acid	Substitution of primary production	Yes	x	x	
marg_iron	kWh/kg Total Wet Weight	Iron recycling	Electricity consumption	Yes	x	x	
marg_pap	kWh/kg Total Wet Weight	Paper recycling	Electricity consumption	Yes	x	x	x
nox_inc	kg/kg Total Wet Weight	Incineration	Nitrogen oxides elementary exchange, process-specific	No	x	x	
nox_pap	kg/kg Total Wet Weight	Paper recycling	Nitrogen oxides, process-specific	No	x	x	x
paper_rec	kg/kg Total Wet Weight	Paper recycling	Substitution of primary production	Yes	x	x	x
paper_seg	%	Source segregation	Percentage of segregated material	No	x	x	x
sox_inc	kg/kg Total Wet Weight	Incineration	Sulphur dioxide elementary exchange, process-specific	No	x	x	
steel_rec	kg/kg Total Wet Weight	Iron recycling	Substitution of primary production	Yes	x	x	
tr_glass_d	km	Transport, glass	Distance driven	Yes	x		x
tr_pap_d	km	Transport, paper	Distance driven	Yes	x		x
tr_pap_d2	km	Transport, paper	Distance driven	Yes	x		x
tr_pap_f	l/kg Total Wet Weight	Transport paper	Fuel consumption	Yes	x		x
tr_rec_f	l/kg Total Wet Weight	Transport recyclables	Fuel consumption	Yes	x		x
tr_res_d	km	Transport, residues	Distance driven	Yes	x	x	x
tr_res_f	l/kg Total Wet Weight	Transport residues	Fuel consumption	Yes	x	x	x
zinc_iron	kg/kg Total Wet Weight	Iron recycling	Zinc, elementary exchange, process specific	No	x	x	
veg_amt	kg	Material generation	Single fraction waste amount	No	x	x	x
ani_amt	kg	Material generation	Single fraction waste amount	No	x	x	x
new_amt	kg	Material generation	Single fraction waste amount	No	x	x	x
adv_amt	kg	Material generation	Single fraction waste amount	No	x	x	x
dia_amt	kg	Material generation	Single fraction waste amount	No	x	x	x
oth_amt	kg	Material generation	Single fraction waste amount	No	x	x	x
pap_amt	kg	Material generation	Single fraction waste amount	No	x	x	x
yar_amt	kg	Material generation	Single fraction waste amount	No	x	x	x
pla_amt	kg	Material generation	Single fraction waste amount	No	x	x	x
dir_amt	kg	Material generation	Single fraction waste amount	No	x	x	x

Table S12. (continued) Complete list of the parameters used in the case studies

Name	Unit	Process	Specific	Linked to an external process	Scenario 1	Scenario 2	Scenario 3
veg_wat	kg water/kg Total Wet Weight	Material generation	Water content by mass, single waste fraction	No	x	x	x
ani_wat	kg water/kg Total Wet Weight	Material generation	Water content by mass, single waste fraction	No	x	x	x
new_wat	kg water/kg Total Wet Weight	Material generation	Water content by mass, single waste fraction	No	x	x	x
adv_wat	kg water/kg Total Wet Weight	Material generation	Water content by mass, single waste fraction	No	x	x	x
dia_wat	kg water/kg Total Wet Weight	Material generation	Water content by mass, single waste fraction	No	x	x	x
oth_wat	kg water/kg Total Wet Weight	Material generation	Water content by mass, single waste fraction	No	x	x	x
pap_wat	kg water/kg Total Wet Weight	Material generation	Water content by mass, single waste fraction	No	x	x	x
yar_wat	kg water/kg Total Wet Weight	Material generation	Water content by mass, single waste fraction	No	x	x	x
pla_wat	kg water/kg Total Wet Weight	Material generation	Water content by mass, single waste fraction	No	x	x	x
dir_wat	kg water/kg Total Wet Weight	Material generation	Water content by mass, single waste fraction	No	x	x	x
veg_ene	MJ/kg TS	Material generation	Energy content by mass, single waste fraction	No	x	x	x
ani_ene	MJ/kg TS	Material generation	Energy content by mass, single waste fraction	No	x	x	x
new_ene	MJ/kg TS	Material generation	Energy content by mass, single waste fraction	No	x	x	x
adv_ene	MJ/kg TS	Material generation	Energy content by mass, single waste fraction	No	x	x	x
dia_ene	MJ/kg TS	Material generation	Energy content by mass, single waste fraction	No	x	x	x
oth_ene	MJ/kg TS	Material generation	Energy content by mass, single waste fraction	No	x	x	x
pap_ene	MJ/kg TS	Material generation	Energy content by mass, single waste fraction	No	x	x	x
yar_ene	MJ/kg TS	Material generation	Energy content by mass, single waste fraction	No	x	x	x
pla_ene	MJ/kg TS	Material generation	Energy content by mass, single waste fraction	No	x	x	x
dir_ene	MJ/kg TS	Material generation	Energy content by mass, single waste fraction	No	x	x	x
veg_fos	kg fossil C/kg TS	Material generation	Fossil carbon content by mass, single waste fraction	No	x	x	x
ani_fos	kg fossil C/kg TS	Material generation	Fossil carbon content by mass, single waste fraction	No	x	x	x
new_fos	kg fossil C/kg TS	Material generation	Fossil carbon content by mass, single waste fraction	No	x	x	x
adv_fos	kg fossil C/kg TS	Material generation	Fossil carbon content by mass, single waste fraction	No	x	x	x
dia_fos	kg fossil C/kg TS	Material generation	Fossil carbon content by mass, single waste fraction	No	x	x	x
oth_fos	kg fossil C/kg TS	Material generation	Fossil carbon content by mass, single waste fraction	No	x	x	x
pap_fos	kg fossil C/kg TS	Material generation	Fossil carbon content by mass, single waste fraction	No	x	x	x
yar_fos	kg fossil C/kg TS	Material generation	Fossil carbon content by mass, single waste fraction	No	x	x	x
pla_fos	kg fossil C/kg TS	Material generation	Fossil carbon content by mass, single waste fraction	No	x	x	x
dir_fos	kg fossil C/kg TS	Material generation	Fossil carbon content by mass, single waste fraction	No	x	x	x
veg_bio	kg bio C/kg TS	Material generation	Biological carbon content by mass, single waste fraction	No	x	x	x
ani_bio	kg bio C/kg TS	Material generation	Biological carbon content by mass, single waste fraction	No	x	x	x
new_bio	kg bio C/kg TS	Material generation	Biological carbon content by mass, single waste fraction	No	x	x	x
adv_bio	kg bio C/kg TS	Material generation	Biological carbon content by mass, single waste fraction	No	x	x	x
dia_bio	kg bio C/kg TS	Material generation	Biological carbon content by mass, single waste fraction	No	x	x	x
oth_bio	kg bio C/kg TS	Material generation	Biological carbon content by mass, single waste fraction	No	x	x	x
pap_bio	kg bio C/kg TS	Material generation	Biological carbon content by mass, single waste fraction	No	x	x	x
yar_bio	kg bio C/kg TS	Material generation	Biological carbon content by mass, single waste fraction	No	x	x	x

Table S12. (continued) Complete list of the parameters used in the case studies

Name	Unit	Process	Specific	Linked to an external process	Scenario 1	Scenario 2	Scenario 3
pla_bio	kg bio C/kg TS	Material generation	Biological carbon content by mass, single waste fraction	No	x	x	x
dir_bio	kg bio C/kg TS	Material generation	Biological carbon content by mass, single waste fraction	No	x	x	x
pret_dig	%	Co-digestion pre-treatment	Segregated bio waste	No		x	
gas_burn	%	Co-digestion, gas leakage	Collected biogas	No		x	
elec_dig	kWh/m3 CH4	Co-digestion, gas utilization	Recovery of electricity	Yes		x	
heat_dig	kWh/m3 CH4	Co-digestion, gas utilization	Recovery of heat	Yes		x	
P_sub	kg/kg P	Fertilizer substitution	Substitution rate	Yes		x	
N_sub	kg/kg N	Fertilizer substitution	Substitution rate	Yes		x	
K_sub	kg/kg K	Fertilizer substitution	Substitution rate	Yes		x	
marg_pret	kWh/kg Total Wet Weight	Co-digestion, pre-treatment	Electricity consumption	Yes		x	
marg_el_gas	kWh/kg Total Wet Weight	Co-digestion, biogas production	Electricity consumption	Yes		x	
marg_h_gas	kWh/kg Total Wet Weight	Co-digestion, biogas production	Heat consumption	Yes		x	
bio_yield	% C bio and	Co-digestion, biogas production	Gas yield as proportion of degradable carbon	No		x	
lossVS	% C bio	LFG - landfill gas generation, moderate conditions	Loss of VS related lo loss of C bio	No			x
heat_rec	kWh/m3 CH4	LFG - Combustion and treatment, energy generation	Recovery of heat	Yes			x
elec_rec	kWh/m3 CH4	LFG - Combustion and treatment, energy generation	Recovery of electricity	Yes			x
met_gas_1	%	LFG - Oxidation in top cover, daily cover	Percentage of released methane	Yes			x
met_gas_2	%	LFG - Oxidation in top cover, intermediate cover	Percentage of released methane	Yes			x
met_gas_3	%	LFG - Oxidation in top cover, final cover	Percentage of released methane	Yes			x
inf	mm/year	Leachate generation	Net infiltration	Yes			x
height	m	Leachate generation	Height of landfill layer	Yes			x
dens	t/m3	Leachate generation	Bulk density	Yes			x
marg_con	kWh/kg Total Wet Weight	Construction and operation of landfill	Electricity consumption	Yes			x
veg_gas	1/year	LFG - landfill gas generation, moderate conditions	First order decay rage for methane generation	No			x
ani_gas	1/year	LFG - landfill gas generation, moderate conditions	First order decay rage for methane generation	No			x
new_gas	1/year	LFG - landfill gas generation, moderate conditions	First order decay rage for methane generation	No			x
adv_gas	1/year	LFG - landfill gas generation, moderate conditions	First order decay rage for methane generation	No			x
dia_gas	1/year	LFG - landfill gas generation, moderate conditions	First order decay rage for methane generation	No			x
oth_gas	1/year	LFG - landfill gas generation, moderate conditions	First order decay rage for methane generation	No			x
pap_gas	1/year	LFG - landfill gas generation, moderate conditions	First order decay rage for methane generation	No			x
yar_gas	1/year	LFG - landfill gas generation, moderate conditions	First order decay rage for methane generation	No			x
dir_gas	1/year	LFG - landfill gas generation, moderate conditions	First order decay rage for methane generation	No			x

SI.3 Instructions on how to provide input uncertainty

This section wants to provide a brief guidance for practitioners on parameters' input uncertainty that we introduce in Eq. (3) in the article. This uncertainty is related to the specific parameters' values due to e.g. inherent variability, measurement imprecision or paucity of data (Clavreul et al., 2012).

Before input uncertainties are systematically propagated into output uncertainties with analytical or sampling methods, the LCA practitioner chooses whether to represent uncertainty according to the probability or possibility theory. The first assumes that all uncertainties can be represented by single probability distributions, thus referring to stochastic uncertainty related to measured data variability and fluctuations. Lloyd and Ries (2007) showed how this choice has been more widely applied, although often poorly justified (e.g. choice of probability distributions without measured data) and relying on estimations. Clavreul et al. (2012) pointed out the domination of epistemic uncertainty in LCA and how possibility theory tools such as min-max intervals and fuzzy sets could be more consistent with paucity of information or personal judgment. A purely statistical representation is thus in order when available information is rich; when information is scarce, a possibility distribution can reflect better the incomplete characteristics of the information available (Clavreul et al. 2013). In the article, the probability theory is applied, as the focus was placed on the uncertainty propagation theory rather than the nature of the data. Heijungs and Tan (2010) analytically propagated fuzzy errors in a matrix-based LCA and Clavreul et al. (2013) compared stochastic and epistemic propagation in LCA.

Ideally, the input uncertainty should be based on measured data on which to build a specific probability distribution function. However, it is a common difficulty to represent the uncertainties of the input data which will be propagated in the model (Laurent et al., 2014b), as complexity of LCA models does not allow to have a set of samples for each of the input parameters. Therefore, when sampling is not possible, probability distributions could be arbitrarily assigned based on the kind of uncertainty and the extent of variability of a specific parameter. In the literature, as evidenced by Laurent et al. (2014b), it is common to assign input uncertainties based on different methods: expert judgment and literature, pedigree matrix as introduced by Frischknecht et al. (2005), a combination of the two, or a simplified approach based on Weidema and Wesnaes (1996). While relating to data quality and to the pedigree matrix imposes the choice of lognormal distributions, a simplified approach could consist in using normal or lognormal distributions when in presence of laboratory analyses, uniform or triangular when in presence of expert opinion (min, max) or (min, max, preferred value).

In any case where no measured data is available, the practitioner could calculate the input variance analytically starting from the value of the parameter and the desired uncertainty range around it. For the present article, the distributions used analytically were:

- Normal
- Lognormal
- Uniform
- Triangular

The choice of these specific distributions allowed comparison between analytically calculated uncertainties and sampled output uncertainties by means of a Monte Carlo analysis carried out with the LCA model EASETECH (Clavreul et al., 2014), since parameters can be modelled with the same distributions in the software. In the next sub-sections we provide a short indication on how to analytically obtain uncertainties for these probability distribution types known the uncertainty range, although large contributions are also easily accessible and available in the internet.

Analytical input variance for normal distributions

The normal distribution is a continuous probability distribution centred on a mean value (μ) and with domain (-∞, ∞). For this reason, in order to express its variance and standard deviation (σ), it is necessary to determine how much of the probability (or the area underlying the probability distribution function curve) we want to represent.

As it can be seen from Figure S8, for the normal distribution, the values less than one standard deviation away from the mean account for 68 % of the set; while two standard deviations from the mean account for 95 %; and three standard deviations account for 99.7 % (Krishnamoorthy and Lian, 2011). Hong et al. (2010) pointed out that in the context of environmental multimedia modelling, a broadly used confidence interval is 95 %.

When the uncertainty range and the probability that we want to represent is known, the standard deviation σ can be easily obtained from the parameter value (which we set as μ). For 95 % confidence interval:

$$\mu' = \mu + 2\sigma$$

Where μ' is a multiple of μ according to the assigned uncertainty range:

$$\mu' = \mu + (\mu \cdot \text{Uncertainty range})$$

The uncertainty range is usually a percentage, e.g. 10 %, 20 %, etc.
The standard deviation σ can then be expressed as:

$$\sigma = \frac{\mu \cdot \text{Uncertainty range}}{2}$$

The corresponding variance is finally obtained as the square of the standard deviation:

$$\sigma^2 = \left(\frac{\mu \cdot \text{Uncertainty range}}{2} \right)^2$$

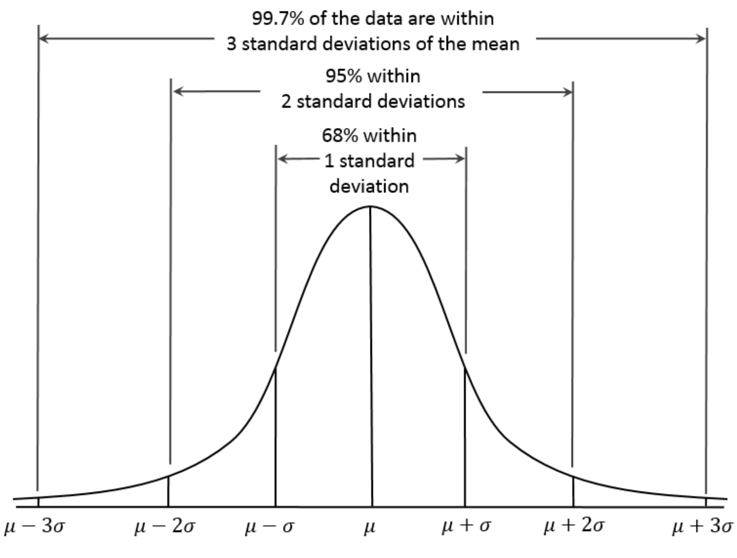


Figure S8. Probability associated with the normal distribution at multiples of the standard deviation. Source for the figure:"Empirical Rule" by Dan Kernler - Own work. Licensed under CC BY-SA 4.0 via Commons - https://commons.wikimedia.org/wiki/File:Empirical_Rule.PNG#/media/File:Empirical_Rule.PNG

Analytical input variance for lognormal distributions

The lognormal distribution is a continuous probability distribution of a random variable whose logarithm is normally distributed (Johnson et al., 1994). Thus, normal and lognormal distributions are closely related. The domain of the lognormal distribution is (0, ∞), needing a confidence interval to be specified in order to express the desired standard deviation.

The lognormal distribution is characterized by the following parameters: geometric mean, geometric standard deviation, geometric variance (Kirkwood and Thomas, 1979). If a variable *X* is distributed lognormally with parameters μ and σ, the geometric mean (*GM*) is given by:

$$GM(X) = e^{\mu}$$

The geometric standard deviation (*GSD*) and geometric variance (*GVAR*):

$$GSD(X) = e^{\sigma}$$

$$GVAR(X) = e^{\sigma^2}$$

The 95 % confidence interval is enclosed by μ/GSD^2 and $\mu \cdot GSD^2$, as shown in Figure S9. These geometric objects can be transformed into arithmetic mean (*E*) and variance (*V*) as follows:

$$E(X) = \exp\left(\mu + \frac{\sigma^2}{2}\right)$$

$$V(X) = \exp\left(2\mu + \sigma^2\right) \cdot \left(\exp\left(\sigma^2\right) - 1\right)$$

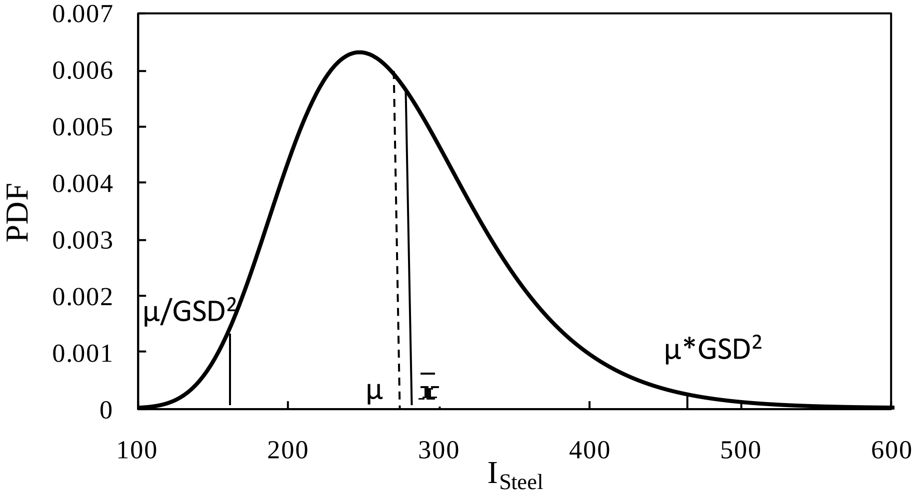


Figure S9. Lognormal distribution for a scenario (steel) as illustrated in Hong et al. (2010). The figure reports geometric mean, mean and 95% confidence interval. Source for the figure: Hong et al. (2010), Supporting information. http://link.springer.com/article/10.1007%2Fs11367-010-0175-4

Note that the geometric mean does not coincide with the maximum of the lognormal curve, nor does the arithmetic mean.

In the case where sampled data are not available, it might be easier to obtain a lognormal distribution for a parameter known its pedigree matrix (Frischknecht et al., 2005), or by transforming an already known (and more intuitive) normal distribution. Then, the mean and standard deviation of the lognormal are given inverting the formulas for E(X) and V(X) (Mathworks, 2015):

$$\mu = \ln\left(\frac{m^2}{\sqrt{v + m^2}}\right)$$

$$\sigma = \sqrt{\ln\left(\frac{v}{m^2} + 1\right)}$$

Where m and v are mean and variance of a normally distributed variable. The variance is thus:

$$\sigma^2 = \ln\left(\frac{v}{m^2} + 1\right)$$

Analytical variance for uniform distributions

The uniform distribution is a continuous probability distribution function with constant probability, whose domain is defined by a minimum and a maximum value (a, b) (Figure S10).

The variance for the distribution can be obtained as a function of the values delimiting the domain (Wolfram, 2015):

$$\sigma^2 = \frac{1}{12}(b-a)^2$$

Knowing the uncertainty range, a and b can be determined from the parameter value μ as:

$$b = \mu + (\mu \cdot \text{Uncertainty range})$$

$$a = \mu - (\mu \cdot \text{Uncertainty range})$$

Note that the uncertainty range does not have to be necessarily symmetrical to the parameter value.

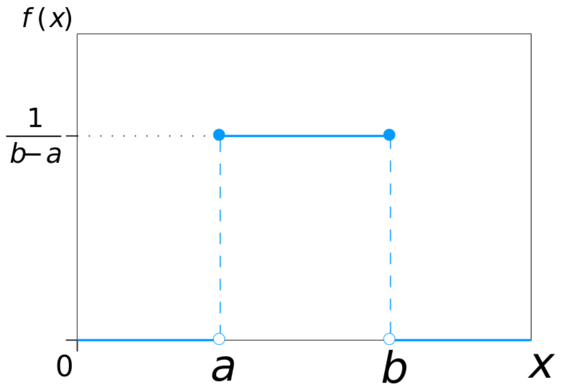


Figure S10. Uniform distribution. Source for the figure: Ikamusume Fan (Own work) [CC BY-SA 3.0 (http://creativecommons.org/licenses/by-sa/3.0)], via Wikimedia Commons

Analytical variance for triangular distributions

The triangular distribution is a continuous probability distribution function whose domain is defined by a minimum and a maximum value (a, b) and a mode c, where where $a < b$ and $a \leq c \leq b$. (Figure S11).

The variance for the distribution can be obtained as a function of the values delimiting the domain and the mode (Evans et al., 2000):

$$\sigma^2 = \frac{1}{18}\left(a^2 + b^2 + c^2 - ab - ac - bc\right)$$

In the case of arbitrarily determined triangular distributions, the mode c is the average value of the parameter of interest (previously called μ). The lower and upper bounds of the distributions can be determined as:

$$b = \mu + (\mu \cdot \text{Uncertainty range})$$

$$a = \mu - (\mu \cdot \text{Uncertainty range})$$

Note that the uncertainty range does not have to be necessarily symmetrical to the parameter value. For specific values of μ, the following special cases can be observed:

- $\mu = \frac{b-a}{2}$ Triangular distribution centred;
- $\mu = a$ Triangular distribution skewed to the left;
- $\mu = b$ Triangular distribution skewed to the right.

In the cases where the mode equals one of the domain limits the triangular distribution has its maximum skewness. The analytical variance is the same in both cases and is equal to:

$$\sigma^2 = \frac{1}{18}\left(a^2 + b^2 - 2ab\right)$$

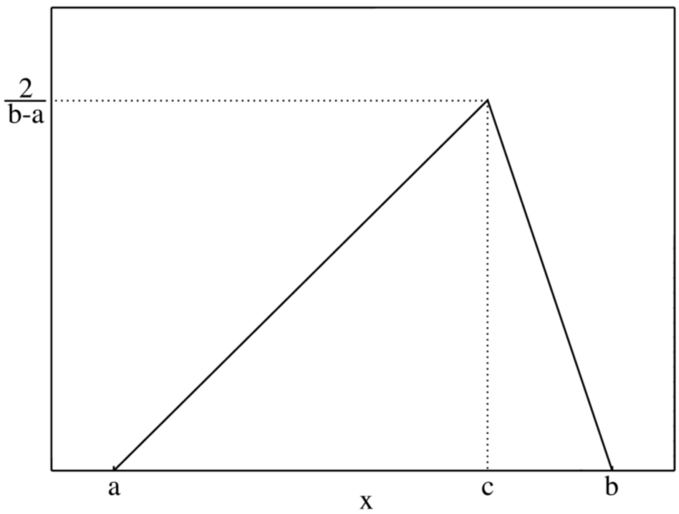


Figure S11. Triangular distribution with minimum, maximum and mode. Source for the figure: "Triangular distribution PMF". Licensed under CC BY-SA 3.0 via Commons - https://commons.wikimedia.org/wiki/File:Triangular_distribution_PMF.png#/media/File:Triangular_distribution_PMF.png

SI.4 Uncertainty propagation: single parameters

Tables S13 – S15 provide the sensitivity ratio (SR), the sensitivity coefficient (SC), the analytical and sampled uncertainty for selected highly sensitive parameters, for all impact categories and waste management scenarios. The sampled uncertainty is calculated with increasing number of Monte Carlo runs (N). Single-parameter analytical and sampled variances are compared by means of the percent difference between the resulting uncertainties.

Table S13. Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters and selected impact categories for scenario 1. The sampled uncertainty results from increasing number of Monte Carlo runs (N)

SCENARIO 1

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo					
				$N=10^3$		$N=10^4$		$N=10^5$	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Global warming potential (GWP)									
elec_rec	5.9E-01	-2.4E-01	**7.1E-06**	7.4E-06	5%	7.2E-06	2%	7.1E-06	0%
veg_wat	-5.1E-01	6.0E-02	**5.4E-06**	5.0E-06	-8%	5.2E-06	-4%	5.1E-06	-5%
paper_rec	4.0E-01	-4.4E-02	**3.4E-06**	3.2E-06	-4%	3.5E-06	3%	3.4E-06	0%
heat_rec	3.3E-01	-4.1E-02	**2.3E-06**	2.3E-06	2%	2.2E-06	0%	2.3E-06	0%
paper_seg	3.2E-01	-5.0E-04	**2.1E-06**	2.0E-06	-4%	2.1E-06	1%	2.1E-06	0%
veg_amt	-2.8E-01	9.6E-05	**1.6E-06**	-	-	-	-	-	-
ani_wat	-1.5E-01	2.4E-02	**4.6E-07**	4.6E-07	-1%	4.4E-07	-4%	4.4E-07	-4%
Ozone depletion potential (ODP)									
alu_rec	9.6E-01	-6.7E-05	**1.0E-11**	9.7E-12	-3%	9.9E-12	0%	9.9E-12	0%
paper_rec	8.8E-02	-6.9E-06	**8.3E-14**	8.4E-14	1%	8.3E-14	0%	8.3E-14	0%
paper_seg	6.3E-02	-7.1E-08	**4.3E-14**	4.5E-14	6%	4.3E-14	0%	4.3E-14	0%
elec_rec	5.5E-02	-1.6E-05	**3.3E-14**	3.4E-14	3%	3.3E-14	-1%	3.3E-14	0%
veg_amt	-4.2E-02	1.1E-08	**1.9E-14**	-	-	-	-	-	-
veg_wat	-3.5E-02	3.0E-06	**1.3E-14**	1.0E-14	-21%	1.0E-14	-23%	1.0E-14	-23%
new_amt	1.7E-02	-1.6E-08	**3.3E-15**	-	-	-	-	-	-
adv_amt	1.6E-02	-1.5E-08	**2.9E-15**	-	-	-	-	-	-
ani_wat	-1.0E-02	1.2E-06	**1.2E-15**	8.6E-16	-28%	9.2E-16	-23%	9.0E-16	-24%
Human toxicity, carcinogenic effects (HTc)									
elec_rec	-5.4E-01	-3.0E-03	**1.1E-09**	1.1E-09	1%	1.1E-09	1%	1.1E-09	0%
paper_rec	-3.6E-01	-5.1E-04	**4.6E-10**	4.4E-10	-5%	4.6E-10	-2%	4.6E-10	0%
paper_seg	-2.8E-01	-5.9E-06	**3.0E-10**	2.7E-10	-10%	2.9E-10	-1%	3.0E-10	0%
veg_wat	2.4E-01	3.8E-04	**2.1E-10**	1.3E-10	-39%	1.4E-10	-35%	1.4E-10	-36%
alu_rec	-2.1E-01	-2.8E-04	**1.7E-10**	1.6E-10	-3%	1.7E-10	1%	1.7E-10	0%
gravel_rec	-1.0E-01	-2.4E-04	**3.7E-11**	3.6E-11	-2%	3.8E-11	1%	3.7E-11	0%
Human toxicity, non-carcinogenic effects (HTnc)									
elec_rec	5.3E+00	-1.8E-02	**3.8E-08**	3.7E-08	-2%	3.8E-08	1%	3.8E-08	0%
paper_rec	5.1E+00	-4.5E-03	**3.5E-08**	3.3E-08	-5%	3.4E-08	-2%	3.5E-08	1%
paper_seg	4.4E+00	-5.6E-05	**2.6E-08**	2.6E-08	-2%	2.6E-08	0%	2.6E-08	0%
veg_wat	-3.5E+00	3.4E-03	**1.7E-08**	1.1E-08	-34%	1.1E-08	-32%	1.1E-08	-33%
veg_amt	-2.6E+00	7.4E-06	**9.4E-09**	0.0E+00	0%	0.0E+00	0%	0.0E+00	0%
alu_rec	2.0E+00	-1.5E-03	**5.3E-09**	5.5E-09	5%	5.2E-09	-1%	5.2E-09	0%
Particulate matter (PM)									
elec_rec	6.0E-01	-5.7E-02	**4.0E-07**	4.2E-07	6%	3.9E-07	-1%	3.9E-07	-1%
veg_wat	-5.0E-01	1.4E-02	**2.7E-07**	1.9E-07	-32%	1.9E-07	-31%	1.9E-07	-31%
paper_rec	3.8E-01	-9.5E-03	**1.6E-07**	1.6E-07	-3%	1.6E-07	2%	1.6E-07	1%
paper_seg	3.0E-01	-1.1E-04	**9.7E-08**	9.5E-08	-2%	9.8E-08	1%	9.7E-08	0%
veg_amt	-2.7E-01	2.1E-05	**8.0E-08**	-	-	-	-	-	-
nox_inc	-2.2E-01	5.5E+00	**5.5E-08**	5.6E-08	2%	5.5E-08	0%	5.5E-08	-1%
heat_rec	1.6E-01	-4.7E-03	**2.9E-08**	2.9E-08	0%	2.8E-08	-3%	2.8E-08	-2%
ani_wat	-1.5E-01	5.4E-03	**2.4E-08**	1.7E-08	-29%	1.6E-08	-32%	1.7E-08	-31%

Table S13. (continues) Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters and selected impact categories for scenario 1. The sampled uncertainty results from increasing number of Monte Carlo runs (N)

SCENARIO 1

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo					
				$N=10^3$		$N=10^4$		$N=10^5$	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Ionizing radiation (IR)									
alu_rec	9.5E-01	-5.5E-03	**6.6E-08**	6.6E-08	1%	6.6E-08	0%	6.6E-08	0%
paper_rec	8.8E-02	-5.7E-04	**5.6E-10**	5.8E-10	3%	5.7E-10	2%	5.6E-10	0%
paper_seg	6.3E-02	-5.9E-06	**2.9E-10**	2.9E-10	-2%	3.0E-10	2%	2.9E-10	0%
elec_rec	5.7E-02	-1.4E-03	**2.4E-10**	2.2E-10	-6%	2.4E-10	1%	2.4E-10	0%
veg_amt	-4.4E-02	9.0E-07	**1.4E-10**	-	-	-	-	-	-
veg_wat	-3.7E-02	2.6E-04	**1.0E-10**	7.4E-11	-27%	7.7E-11	-24%	7.8E-11	-23%
new_amt	1.7E-02	-1.3E-06	**2.1E-11**	-	-	-	-	-	-
adv_amt	1.7E-02	-1.3E-06	**2.0E-11**	-	-	-	-	-	-
gravel_rec	1.4E-02	-1.5E-04	**1.4E-11**	1.3E-11	-7%	1.4E-11	1%	1.4E-11	0%
Photochemical ozone formation (POFP)									
nox_inc	-2.1E+00	1.5E+01	**3.9E-07**	3.8E-07	-3%	3.9E-07	1%	3.9E-07	0%
heat_rec	2.0E+00	-1.6E-02	**3.5E-07**	3.4E-07	-5%	3.5E-07	-1%	3.5E-07	0%
veg_wat	-2.0E+00	1.5E-02	**3.4E-07**	2.3E-07	-32%	2.5E-07	-28%	2.5E-07	-28%
elec_rec	1.1E+00	-2.8E-02	**9.8E-08**	9.9E-08	1%	9.6E-08	-2%	9.8E-08	0%
veg_amt	-6.6E-01	1.5E-05	**3.8E-08**	-	-	-	-	-	-
ani_wat	-5.9E-01	6.1E-03	**3.0E-08**	2.2E-08	-28%	2.1E-08	-29%	2.2E-08	-29%
veg_ene	4.5E-01	-1.4E-04	**1.7E-08**	1.6E-08	-4%	1.7E-08	1%	1.7E-08	0%
pla_ene	4.3E-01	-6.9E-05	**1.6E-08**	1.6E-08	-1%	1.6E-08	2%	1.6E-08	1%
Terrestrial acidification (TA)									
heat_rec	6.5E-01	-2.9E-02	**1.1E-06**	1.1E-06	2%	1.1E-06	1%	1.1E-06	1%
veg_wat	-6.5E-01	2.7E-02	**1.1E-06**	7.6E-07	-31%	7.7E-07	-31%	7.7E-07	-30%
elec_rec	3.4E-01	-5.0E-02	**3.0E-07**	3.2E-07	8%	2.9E-07	-2%	3.0E-07	1%
nox_inc	-3.3E-01	1.2E+01	**2.8E-07**	2.8E-07	1%	2.7E-07	-2%	2.8E-07	-1%
veg_amt	-2.2E-01	2.7E-05	**1.3E-07**	-	-	-	-	-	-
glass_rec	2.0E-01	-7.2E-03	**1.0E-07**	1.1E-07	10%	1.0E-07	0%	1.0E-07	0%
ani_wat	-1.9E-01	1.1E-02	**9.9E-08**	6.5E-08	-34%	6.8E-08	-31%	6.8E-08	-31%
alu_rec	1.6E-01	-5.7E-03	**7.1E-08**	7.0E-08	-2%	7.0E-08	-1%	7.1E-08	0%
Terrestrial eutrophication (TE)									
nox_inc	-3.2E+00	3.1E+01	**1.7E-06**	1.6E-06	-6%	1.7E-06	-2%	1.7E-06	-1%
heat_rec	2.9E+00	-3.2E-02	**1.4E-06**	1.4E-06	-2%	1.3E-06	-3%	1.4E-06	-1%
veg_wat	-2.7E+00	2.9E-02	**1.3E-06**	9.1E-07	-29%	9.2E-07	-28%	9.2E-07	-28%
elec_rec	1.4E+00	-5.3E-02	**3.3E-07**	3.1E-07	-6%	3.2E-07	-3%	3.3E-07	0%
veg_amt	-8.9E-01	2.8E-05	**1.3E-07**	-	-	-	-	-	-
ani_wat	-8.2E-01	1.2E-02	**1.1E-07**	7.8E-08	-31%	8.2E-08	-27%	8.2E-08	-28%
veg_ene	6.2E-01	-2.8E-04	**6.4E-08**	6.4E-08	0%	6.3E-08	-1%	6.4E-08	0%
pla_ene	5.9E-01	-1.3E-04	**5.9E-08**	5.7E-08	-3%	5.9E-08	0%	5.9E-08	0%

Table S13. (continues) Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters and selected impact categories for scenario 1. The sampled uncertainty results from increasing number of Monte Carlo runs (N)

SCENARIO 1

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo					
				$N=10^3$		$N=10^4$		$N=10^5$	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Freshwater eutrophication (FE)									
glass_rec	9.7E-01	-6.9E-04	**9.5E-10**	1.0E-09	7%	9.5E-10	0%	9.5E-10	1%
glass_seg	9.7E-01	-8.5E-06	**9.4E-10**	1.0E-09	6%	9.6E-10	2%	9.5E-10	1%
paper_rec	1.3E-01	-1.0E-04	**1.8E-11**	1.8E-11	2%	1.8E-11	0%	1.8E-11	0%
paper_seg	3.2E-02	-3.5E-07	**1.0E-12**	9.5E-13	-8%	1.1E-12	2%	1.1E-12	2%
veg_amt	-1.3E-02	3.0E-08	**1.6E-13**	-	-	-	-	-	-
new_amt	8.0E-03	-7.1E-08	**6.5E-14**	-	-	-	-	-	-
adv_amt	7.8E-03	-7.1E-08	**6.0E-14**	-	-	-	-	-	-
oth_amt	4.8E-03	-7.0E-08	**2.3E-14**	-	-	-	-	-	-
ani_amt	-3.9E-03	3.0E-08	**1.5E-14**	-	-	-	-	-	-
gravel_rec	2.9E-03	-3.7E-06	**8.4E-15**	8.2E-15	-3%	8.3E-15	0%	8.3E-15	-1%
dia_amt	-2.2E-03	3.0E-08	**4.7E-15**	-	-	-	-	-	-
pap_amt	-2.1E-03	3.1E-08	**4.3E-15**	-	-	-	-	-	-
yar_amt	-1.6E-03	3.0E-08	**2.6E-15**	-	-	-	-	-	-
pla_amt	-1.5E-03	2.9E-08	**2.3E-15**	-	-	-	-	-	-
dir_amt	-1.2E-03	3.1E-08	**1.5E-15**	-	-	-	-	-	-
elec_rec	1.1E-03	-3.1E-06	**1.2E-15**	1.1E-15	-6%	1.2E-15	0%	1.2E-15	-1%
Marine eutrophication (ME)									
nox_inc	-3.1E+00	3.5E+01	**2.2E-06**	2.2E-06	3%	2.1E-06	-1%	2.2E-06	0%
heat_rec	2.7E+00	-3.6E-02	**1.7E-06**	1.8E-06	1%	1.7E-06	0%	1.7E-06	1%
veg_wat	-2.6E+00	3.3E-02	**1.6E-06**	1.1E-06	-31%	1.2E-06	-27%	1.1E-06	-28%
elec_rec	1.3E+00	-5.8E-02	**4.1E-07**	4.4E-07	7%	4.2E-07	2%	4.1E-07	0%
veg_amt	-8.8E-01	3.2E-05	**1.8E-07**	-	-	-	-	-	-
ani_wat	-7.9E-01	1.3E-02	**1.4E-07**	1.0E-07	-27%	1.0E-07	-29%	1.0E-07	-28%
veg_ene	5.9E-01	-3.1E-04	**8.0E-08**	8.3E-08	3%	8.0E-08	0%	8.0E-08	0%
pla_ene	5.7E-01	-1.5E-04	**7.4E-08**	7.7E-08	4%	7.4E-08	0%	7.3E-08	0%
Freshwater ecotoxicity (ET)									
paper_rec	1.4E+00	-7.8E-02	**1.1E-05**	1.1E-05	2%	1.1E-05	-2%	1.1E-05	-1%
paper_seg	1.4E+00	-1.1E-03	**1.1E-05**	1.0E-05	-3%	1.1E-05	-1%	1.1E-05	0%
veg_amt	-5.8E-01	1.0E-04	**1.8E-06**	-	-	-	-	-	-
cop_inc	-3.8E-01	6.9E+04	**7.4E-07**	8.4E-07	14%	7.5E-07	1%	7.5E-07	1%
new_amt	3.7E-01	-2.4E-04	**7.1E-07**	-	-	-	-	-	-
adv_amt	3.5E-01	-2.3E-04	**6.4E-07**	-	-	-	-	-	-
oth_amt	2.2E-01	-2.3E-04	**2.6E-07**	-	-	-	-	-	-
ani_amt	-1.8E-01	1.0E-04	**1.7E-07**	-	-	-	-	-	-
dia_amt	-9.9E-02	1.0E-04	**5.2E-08**	-	-	-	-	-	-
pap_amt	-9.7E-02	1.1E-04	**4.9E-08**	-	-	-	-	-	-
yar_amt	-7.8E-02	1.1E-04	**3.2E-08**	-	-	-	-	-	-
alu_rec	7.1E-02	-3.4E-03	**2.6E-08**	2.7E-08	2%	2.6E-08	1%	2.6E-08	0%
dir_amt	-5.5E-02	9.9E-05	**1.6E-08**	-	-	-	-	-	-
pla_amt	-5.3E-02	7.5E-05	**1.5E-08**	-	-	-	-	-	-
elec_rec	3.5E-02	-7.3E-03	**6.4E-09**	6.2E-09	-4%	6.0E-09	-6%	6.0E-09	-6%
glass_rec	3.3E-02	-1.7E-03	**5.6E-09**	5.3E-09	-4%	5.5E-09	-1%	5.6E-09	0%

Table S13. (continues) Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters and selected impact categories for scenario 1. The sampled uncertainty results from increasing number of Monte Carlo runs (N)

SCENARIO 1

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo					
				$N=10^3$		$N=10^4$		$N=10^5$	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Resource depletion, fossil (Rdfos)									
elec_rec	1.1E+00	-4.0E-01	**1.9E-05**	2.0E-05	5%	1.9E-05	0%	1.9E-05	0%
veg_wat	-7.2E-01	7.3E-02	**8.0E-06**	5.2E-06	-35%	5.4E-06	-32%	5.5E-06	-31%
paper_rec	7.0E-01	-6.6E-02	**7.6E-06**	7.1E-06	-6%	7.7E-06	2%	7.6E-06	-1%
paper_seg	4.0E-01	-5.4E-04	**2.4E-06**	2.4E-06	-1%	2.4E-06	-1%	2.4E-06	0%
veg_amt	-3.7E-01	1.1E-04	**2.2E-06**	-	-	-	-	-	-
coll_res	-2.2E-01	5.3E-03	**7.4E-07**	7.6E-07	3%	7.4E-07	0%	7.4E-07	0%
ani_wat	-2.1E-01	2.9E-02	**7.0E-07**	5.2E-07	-25%	4.7E-07	-33%	4.8E-07	-31%
Resource depletion (RD)									
gravel_rec	1.2E+00	-4.6E-05	**1.3E-12**	1.3E-12	2%	1.3E-12	2%	1.3E-12	0%
veg_amt	-2.0E-01	1.4E-08	**3.6E-14**	-	-	-	-	-	-
veg_wat	-1.5E-01	3.7E-06	**2.0E-14**	1.8E-14	-12%	1.7E-14	-15%	1.7E-14	-16%
ani_wat	-5.5E-02	1.8E-06	**2.8E-15**	2.5E-15	-8%	2.4E-15	-12%	2.5E-15	-10%
adv_amt	5.3E-02	-1.5E-08	**2.6E-15**	-	-	-	-	-	-
yar_wat	-5.2E-02	2.0E-06	**2.4E-15**	2.1E-15	-12%	2.3E-15	-6%	2.2E-15	-7%
ani_amt	-3.2E-02	7.5E-09	**9.3E-16**	-	-	-	-	-	-
yar_amt	2.9E-02	-1.6E-08	**7.6E-16**	-	-	-	-	-	-
new_amt	-2.5E-02	6.7E-09	**5.8E-16**	-	-	-	-	-	-
dia_wat	-2.5E-02	1.0E-06	**5.5E-16**	4.4E-16	-21%	4.4E-16	-20%	4.5E-16	-19%
pap_amt	2.3E-02	-1.0E-08	**4.8E-16**	-	-	-	-	-	-
pap_wat	-2.0E-02	1.7E-06	**3.6E-16**	2.4E-16	-35%	2.3E-16	-36%	2.4E-16	-35%

Table S14. Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters and selected impact categories for scenario 2. The sampled uncertainty results from increasing number of Monte Carlo runs (N)

SCENARIO 2

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo N=10^3		N=10^4		N=10^5	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Global warming potential (GWP)									
elec_rec	5.4E-01	-2.1E-01	**5.2E-06**	5.7E-06	10%	5.4E-06	3%	5.4E-06	3%
paper_rec	4.3E-01	-4.3E-02	**3.3E-06**	3.2E-06	0%	3.4E-06	5%	3.4E-06	3%
veg_wat	-3.8E-01	4.2E-02	**2.6E-06**	2.6E-06	0%	2.5E-06	-2%	2.4E-06	-4%
paper_seg	3.4E-01	-4.9E-04	**2.0E-06**	2.1E-06	6%	2.1E-06	7%	2.1E-06	6%
veg_amt	-3.1E-01	1.0E-04	**1.8E-06**	-	-	-	-	-	-
heat_rec	3.0E-01	-3.5E-02	**1.6E-06**	1.7E-06	3%	1.7E-06	7%	1.7E-06	4%
pla_ene	1.3E-01	-3.0E-04	**3.0E-07**	3.3E-07	10%	3.3E-07	12%	3.3E-07	12%
Ozone depletion potential (ODP)									
alu_rec	9.5E-01	-6.7E-05	**1.0E-11**	1.0E-11	2%	1.0E-11	2%	9.9E-12	0%
paper_rec	8.6E-02	-6.9E-06	**8.3E-14**	8.2E-14	-1%	8.2E-14	-1%	8.3E-14	0%
paper_seg	6.2E-02	-7.1E-08	**4.3E-14**	4.0E-14	-7%	4.3E-14	0%	4.3E-14	1%
elec_rec	4.7E-02	-1.4E-05	**2.5E-14**	2.7E-14	7%	2.5E-14	1%	2.5E-14	0%
veg_amt	-3.6E-02	9.1E-09	**1.4E-14**	-	-	-	-	-	-
veg_wat	-2.3E-02	2.0E-06	**6.1E-15**	6.2E-15	2%	6.1E-15	0%	6.1E-15	1%
new_amt	1.5E-02	-1.4E-08	**2.6E-15**	-	-	-	-	-	-
adv_amt	1.4E-02	-1.4E-08	**2.3E-15**	-	-	-	-	-	-
oth_amt	1.0E-02	-1.6E-08	**1.2E-15**	-	-	-	-	-	-
ani_amt	-8.1E-03	6.7E-09	**7.3E-16**	-	-	-	-	-	-
pla_ene	7.5E-03	-1.4E-08	**6.3E-16**	6.8E-16	7%	6.3E-16	0%	6.3E-16	0%
Human toxicity, carcinogenic effects (HTc)									
pret_dig	7.1E-01	3.7E-05	**1.9E-08**	1.9E-08	-2%	1.9E-08	-1%	1.9E-08	1%
yar_amt	3.5E-01	4.1E-05	**4.7E-09**	-	-	-	-	-	-
yar_wat	-3.2E-01	-2.6E-03	**3.9E-09**	3.9E-09	-1%	3.9E-09	1%	3.9E-09	0%
veg_wat	-2.4E-01	-1.2E-03	**2.1E-09**	2.2E-09	3%	2.2E-09	4%	2.1E-09	1%
veg_amt	-1.6E-01	-2.4E-06	**1.0E-09**	-	-	-	-	-	-
elec_rec	-1.5E-01	-2.6E-03	**8.2E-10**	8.3E-10	2%	8.3E-10	2%	8.1E-10	0%
ani_amt	-1.2E-01	-5.9E-06	**5.6E-10**	-	-	-	-	-	-
paper_rec	-1.1E-01	-5.1E-04	**4.6E-10**	4.6E-10	0%	4.6E-10	-1%	4.6E-10	0%
new_amt	-1.0E-01	-5.6E-06	**4.0E-10**	-	-	-	-	-	-
paper_seg	-8.9E-02	-5.9E-06	**3.0E-10**	2.9E-10	-3%	2.9E-10	-1%	3.0E-10	0%
Human toxicity, non-carcinogenic effects (HTnc)									
pret_dig	1.0E+00	2.8E-03	**1.1E-04**	1.1E-04	1%	1.1E-04	0%	1.1E-04	0%
veg_wat	-4.8E-01	-1.3E-01	**2.6E-05**	2.6E-05	0%	2.6E-05	1%	2.6E-05	0%
yar_amt	4.2E-01	2.7E-03	**2.0E-05**	-	-	-	-	-	-
yar_wat	-4.0E-01	-1.8E-01	**1.8E-05**	1.9E-05	8%	1.8E-05	1%	1.8E-05	2%
veg_amt	-2.6E-01	-2.1E-04	**7.8E-06**	-	-	-	-	-	-
ani_wat	-1.7E-01	-6.3E-02	**3.3E-06**	3.5E-06	6%	3.3E-06	1%	3.4E-06	5%
new_amt	-1.2E-01	-3.6E-04	**1.7E-06**	-	-	-	-	-	-
adv_amt	-1.2E-01	-3.6E-04	**1.6E-06**	-	-	-	-	-	-
dia_amt	-7.4E-02	-3.5E-04	**6.2E-07**	-	-	-	-	-	-
oth_amt	-7.2E-02	-3.5E-04	**5.9E-07**	-	-	-	-	-	-
pap_amt	-6.5E-02	-3.3E-04	**4.8E-07**	-	-	-	-	-	-
dir_amt	-3.9E-02	-3.3E-04	**1.7E-07**	-	-	-	-	-	-
paper_rec	-1.8E-02	-4.5E-03	**3.5E-08**	3.8E-08	9%	3.6E-08	2%	3.5E-08	0%
ani_amt	1.8E-02	4.6E-05	**3.5E-08**	-	-	-	-	-	-
elec_rec	-1.6E-02	-1.5E-02	**2.9E-08**	2.8E-08	-4%	2.6E-08	-9%	2.9E-08	1%

Table S14. (continues) Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters and selected impact categories for scenario 2. The sampled uncertainty results from increasing number of Monte Carlo runs (N)

SCENARIO 2

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo					
				$N=10^3$		$N=10^4$		$N=10^5$	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Particulate matter (PM)									
elec_rec	5.1E-01	-4.9E-02	**3.0E-07**	3.1E-07	4%	3.0E-07	0%	3.0E-07	0%
paper_rec	3.8E-01	-9.5E-03	**1.6E-07**	1.6E-07	-1%	1.6E-07	-1%	1.6E-07	0%
veg_amt	-3.1E-01	2.5E-05	**1.1E-07**	-	-	-	-	-	-
veg_wat	-3.0E-01	8.1E-03	**9.8E-08**	9.0E-08	-9%	9.8E-08	0%	9.8E-08	0%
paper_seg	2.9E-01	-1.1E-04	**9.7E-08**	9.8E-08	1%	9.8E-08	1%	9.7E-08	0%
nox_inc	-1.6E-01	4.0E+00	**2.8E-08**	2.8E-08	-2%	2.9E-08	4%	2.8E-08	0%
alu_rec	1.4E-01	-3.2E-03	**2.2E-08**	2.0E-08	-8%	2.3E-08	2%	2.2E-08	-1%
heat_rec	1.4E-01	-4.0E-03	**2.1E-08**	2.1E-08	-2%	2.1E-08	0%	2.1E-08	0%
Ionizing radiation (IR)									
alu_rec	9.3E-01	-5.4E-03	**6.6E-08**	6.8E-08	3%	6.5E-08	0%	6.5E-08	0%
paper_rec	8.7E-02	-5.7E-04	**5.6E-10**	5.9E-10	5%	5.6E-10	0%	5.7E-10	1%
paper_seg	6.3E-02	-5.9E-06	**2.9E-10**	3.1E-10	5%	3.0E-10	1%	2.9E-10	0%
elec_rec	4.9E-02	-1.2E-03	**1.8E-10**	1.6E-10	-8%	1.8E-10	0%	1.8E-10	0%
veg_amt	-3.8E-02	7.9E-07	**1.1E-10**	-	-	-	-	-	-
veg_wat	-2.5E-02	1.7E-04	**4.5E-11**	4.5E-11	-2%	4.4E-11	-2%	4.5E-11	-1%
new_amt	1.5E-02	-1.2E-06	**1.7E-11**	-	-	-	-	-	-
adv_amt	1.5E-02	-1.2E-06	**1.6E-11**	-	-	-	-	-	-
gravel_rec	1.2E-02	-1.3E-04	**1.1E-11**	1.1E-11	0%	1.1E-11	2%	1.1E-11	-1%
Photochemical ozone formation (POFP)									
heat_rec	-1.2E+00	1.1E+01	**2.0E-07**	2.0E-07	-2%	2.0E-07	1%	2.0E-07	0%
nox_inc	-8.6E-01	8.2E-03	**9.9E-08**	9.9E-08	0%	9.9E-08	0%	9.9E-08	0%
veg_wat	7.5E-01	-2.5E-02	**7.4E-08**	7.1E-08	-5%	7.4E-08	0%	7.4E-08	-1%
elec_rec	-5.8E-01	1.6E-05	**4.5E-08**	0.0E+00	0%	0.0E+00	0%	0.0E+00	0%
veg_amt	3.4E-01	-6.9E-05	**1.6E-08**	-	-	-	-	-	-
pla_ene	3.0E-01	-2.5E-03	**1.2E-08**	1.3E-08	3%	1.2E-08	1%	1.2E-08	0%
glass_rec	-2.5E-01	3.2E-03	**8.6E-09**	9.1E-09	6%	8.5E-09	-2%	8.6E-09	0%
ani_wat	2.5E-01	-5.7E-05	**8.6E-09**	0.0E+00	0%	0.0E+00	0%	0.0E+00	0%
Terrestrial acidification (TA)									
heat_rec	5.7E-01	-2.5E-02	**8.4E-07**	8.7E-07	4%	8.7E-07	3%	8.5E-07	1%
veg_wat	-3.4E-01	1.4E-02	**3.0E-07**	2.9E-07	-5%	3.0E-07	1%	3.0E-07	0%
elec_rec	3.0E-01	-4.3E-02	**2.3E-07**	2.3E-07	0%	2.2E-07	-4%	2.3E-07	-1%
veg_amt	-2.9E-01	3.6E-05	**2.2E-07**	-	-	-	-	-	-
nox_inc	-2.4E-01	9.0E+00	**1.5E-07**	1.4E-07	-6%	1.4E-07	-4%	1.4E-07	-2%
glass_rec	2.0E-01	-7.2E-03	**1.0E-07**	1.0E-07	-2%	1.0E-07	-1%	1.0E-07	0%
alu_rec	1.6E-01	-5.7E-03	**7.1E-08**	6.4E-08	-10%	7.1E-08	0%	7.1E-08	0%
glass_seg	1.5E-01	-6.9E-05	**6.2E-08**	6.4E-08	3%	6.2E-08	0%	6.2E-08	0%
Terrestrial eutrophication (TE)									
heat_rec	1.9E+00	-2.8E-02	**1.1E-06**	1.0E-06	-2%	1.1E-06	2%	1.0E-06	0%
nox_inc	-1.7E+00	2.2E+01	**8.8E-07**	8.9E-07	0%	8.9E-07	1%	8.9E-07	0%
veg_wat	-1.1E+00	1.5E-02	**3.3E-07**	3.3E-07	0%	3.4E-07	1%	3.3E-07	0%
elec_rec	9.3E-01	-4.6E-02	**2.5E-07**	2.4E-07	-6%	2.6E-07	2%	2.5E-07	0%
veg_amt	-7.0E-01	2.9E-05	**1.4E-07**	-	-	-	-	-	-
pla_ene	4.5E-01	-1.3E-04	**5.9E-08**	6.4E-08	7%	5.9E-08	-1%	5.9E-08	-1%
glass_rec	4.4E-01	-5.3E-03	**5.6E-08**	5.8E-08	3%	5.6E-08	0%	5.6E-08	0%

Table S14. (continues) Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters and selected impact categories for scenario 2. The sampled uncertainty results from increasing number of Monte Carlo runs (N)

SCENARIO 2

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo N=10^3		N=10^4		N=10^5	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Freshwater eutrophication (FE)									
P_sub	-7.9E-01	2.5E-03	**1.5E-08**	1.5E-08	0%	1.5E-08	0%	1.5E-08	0%
pret_dig	7.9E-01	-3.3E-05	**1.5E-08**	1.5E-08	2%	1.5E-08	-1%	1.5E-08	1%
veg_wat	-6.2E-01	2.5E-03	**9.1E-09**	8.0E-09	-12%	9.2E-09	1%	9.2E-09	0%
ani_wat	-6.1E-01	3.3E-03	**8.8E-09**	5.4E-07	0%	9.0E-09	1%	8.8E-09	0%
ani_amt	4.4E-01	-1.7E-05	**4.6E-09**	-	-	-	-	-	-
glass_rec	2.0E-01	-6.9E-04	**9.5E-10**	9.0E-10	-5%	9.5E-10	1%	9.5E-10	0%
glass_seg	2.0E-01	-8.5E-06	**9.4E-10**	9.5E-10	1%	9.3E-10	-1%	9.5E-10	1%
Marine eutrophication (ME)									
pret_dig	1.8E+00	3.8E-04	**2.0E-06**	2.1E-06	5%	2.1E-06	0%	2.0E-06	0%
heat_rec	-1.5E+00	-3.1E-02	**1.3E-06**	1.4E-06	4%	1.3E-06	-2%	1.3E-06	0%
nox_inc	1.3E+00	2.5E+01	**1.1E-06**	1.1E-06	0%	1.1E-06	-1%	1.1E-06	1%
ani_wat	-1.2E+00	-3.3E-02	**9.1E-07**	9.6E-07	5%	9.2E-07	1%	9.1E-07	0%
ani_amt	1.1E+00	2.1E-04	**7.5E-07**	-	-	-	-	-	-
veg_wat	-8.7E-01	-1.8E-02	**4.7E-07**	5.1E-07	7%	4.9E-07	4%	4.8E-07	1%
elec_rec	-7.1E-01	-5.1E-02	**3.1E-07**	3.3E-07	6%	3.1E-07	0%	3.2E-07	1%
veg_amt	5.8E-01	3.5E-05	**2.1E-07**	-	-	-	-	-	-
pla_ene	-3.4E-01	-1.5E-04	**7.3E-08**	7.8E-08	7%	7.3E-08	1%	7.4E-08	3%
Freshwater ecotoxicity (ET)									
pret_dig	1.3E+00	2.9E-03	**1.2E-04**	1.3E-04	11%	0.0E+00	0%	0.0E+00	0%
veg_wat	-8.2E-01	-1.8E-01	**4.8E-05**	2.2E-04	367%	0.0E+00	0%	0.0E+00	0%
yar_amt	4.3E-01	2.2E-03	**1.3E-05**	-	-	-	-	-	-
yar_wat	-4.0E-01	-1.4E-01	**1.1E-05**	1.0E-05	-9%	0.0E+00	0%	0.0E+00	0%
paper_rec	-3.9E-01	-7.8E-02	**1.1E-05**	1.1E-05	2%	0.0E+00	0%	0.0E+00	0%
paper_seg	-3.9E-01	-1.1E-03	**1.1E-05**	1.0E-05	-4%	0.0E+00	0%	0.0E+00	0%
new_amt	-2.3E-01	-5.3E-04	**3.6E-06**	-	-	-	-	-	-
adv_amt	-2.1E-01	-5.2E-04	**3.3E-06**	-	-	-	-	-	-
ani_wat	-1.9E-01	-5.6E-02	**2.6E-06**	2.6E-06	0%	0.0E+00	0%	0.0E+00	0%
Resource depletion, fossil (Rdfos)									
elec_rec	1.2E+00	-3.4E-01	**1.4E-05**	1.4E-05	-4%	1.4E-05	0%	1.4E-05	0%
paper_rec	8.7E-01	-6.6E-02	**7.6E-06**	7.9E-06	4%	7.5E-06	-1%	7.6E-06	0%
veg_amt	-6.8E-01	1.6E-04	**4.6E-06**	-	-	-	-	-	-
veg_wat	-5.9E-01	4.9E-02	**3.5E-06**	3.7E-06	4%	3.6E-06	1%	3.5E-06	0%
paper_seg	4.9E-01	-5.4E-04	**2.4E-06**	2.3E-06	-6%	2.4E-06	-2%	2.4E-06	0%
pla_ene	1.9E-01	-3.3E-04	**3.6E-07**	3.5E-07	-3%	3.6E-07	1%	3.6E-07	0%
coll_res	-1.6E-01	3.1E-03	**2.7E-07**	2.9E-07	8%	2.6E-07	0%	2.7E-07	1%
Resource depletion (RD)									
gravel_rec	1.2E+00	-4.0E-05	**1.0E-12**	9.4E-13	-8%	1.0E-12	2%	1.0E-12	0%
veg_amt	-2.0E-01	1.3E-08	**3.0E-14**	-	-	-	-	-	-
veg_wat	-7.1E-02	1.6E-06	**3.6E-15**	3.9E-15	11%	3.8E-15	7%	3.9E-15	10%
adv_amt	6.3E-02	-1.5E-08	**2.9E-15**	-	-	-	-	-	-
ani_amt	-4.9E-02	1.0E-08	**1.7E-15**	-	-	-	-	-	-
pap_amt	3.0E-02	-1.2E-08	**6.6E-16**	-	-	-	-	-	-
pret_dig	-2.5E-02	5.6E-09	**4.3E-16**	4.2E-16	-4%	4.5E-16	3%	4.3E-16	0%
dia_wat	-2.4E-02	9.0E-07	**4.2E-16**	4.7E-16	12%	4.5E-16	7%	4.4E-16	5%
ani_wat	-2.4E-02	7.0E-07	**4.0E-16**	5.0E-16	24%	5.2E-16	29%	5.2E-16	29%
yar_wat	-2.2E-02	7.7E-07	**3.5E-16**	4.3E-16	24%	4.4E-16	26%	4.4E-16	25%

Table S15. Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters and selected impact categories for scenario 3. The sampled uncertainty results from increasing number of Monte Carlo runs (N)

SCENARIO 3

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo N=10^3		N=10^4		N=10^5	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Global warming potential (GWP)									
veg_wat	3.2E+00	-7.4E-02	**8.0E-06**	8.1E-06	1%	7.9E-06	-2%	8.1E-06	1%
paper_rec	2.1E+00	-4.4E-02	**3.4E-06**	3.3E-06	-2%	3.4E-06	0%	3.4E-06	1%
met_gas_1	-1.9E+00	3.7E-04	**2.8E-06**	2.8E-06	2%	2.8E-06	0%	2.8E-06	0%
veg_amt	-1.8E+00	1.2E-04	**2.5E-06**	-	-	-	-	-	-
paper_seg	1.7E+00	-5.0E-04	**2.1E-06**	2.0E-06	-4%	2.1E-06	1%	2.1E-06	0%
veg_bio	-9.7E-01	3.6E-02	**7.3E-07**	6.9E-07	-6%	7.4E-07	1%	7.3E-07	0%
met_gas_3	-9.5E-01	2.6E-04	**6.9E-07**	6.8E-07	-1%	6.9E-07	0%	6.8E-07	-1%
Ozone depletion potential (ODP)									
veg_wat	-1.3E+00	-1.3E-03	**2.7E-09**	2.8E-09	4%	2.7E-09	1%	2.7E-09	0%
veg_bio	3.8E-01	6.5E-04	**2.4E-10**	2.4E-10	2%	2.3E-10	-1%	2.4E-10	2%
ani_wat	-2.5E-01	-3.5E-04	**1.0E-10**	1.1E-10	9%	1.0E-10	1%	1.0E-10	0%
ani_bio	1.8E-01	2.7E-04	**5.6E-11**	5.5E-11	-2%	5.5E-11	-2%	5.7E-11	1%
veg_amt	1.1E-01	3.5E-07	**2.1E-11**	-	-	-	-	-	-
ani_amt	1.1E-01	1.1E-06	**2.0E-11**	-	-	-	-	-	-
veg_gas	8.5E-02	5.0E-04	**1.2E-11**	1.2E-11	0%	1.3E-11	6%	1.3E-11	5%
pap_bio	7.4E-02	1.5E-04	**9.0E-12**	8.6E-12	-4%	9.3E-12	4%	9.3E-12	3%
Human toxicity, carcinogenic effects (HTc)									
inf	1.0E+00	4.0E-05	**3.7E-07**	3.5E-07	-4%	3.7E-07	0%	3.7E-07	0%
height	-9.3E-01	-1.1E-03	**3.0E-07**	3.9E-07	27%	3.8E-07	24%	3.7E-07	23%
dens	-9.3E-01	-1.1E-02	**3.0E-07**	4.0E-07	30%	3.8E-07	25%	3.7E-07	22%
veg_wat	2.3E-01	3.5E-03	**1.8E-08**	1.8E-08	1%	1.8E-08	1%	1.8E-08	0%
lossVS	-1.8E-01	-1.1E-03	**1.1E-08**	1.1E-08	2%	1.1E-08	1%	1.1E-08	-1%
veg_bio	-7.6E-02	-1.9E-03	**2.0E-09**	1.7E-09	-15%	1.7E-09	-13%	1.8E-09	-8%
Human toxicity, non-carcinogenic effects (HTnc)									
paper_rec	1.7E+00	-4.5E-03	**3.5E-08**	3.3E-08	-4%	3.6E-08	3%	3.5E-08	0%
paper_seg	1.4E+00	-5.6E-05	**2.6E-08**	2.5E-08	-6%	2.7E-08	1%	2.7E-08	1%
inf	-7.3E-01	5.5E-06	**6.7E-09**	7.3E-09	8%	6.7E-09	0%	6.7E-09	0%
height	6.7E-01	-1.5E-04	**5.6E-09**	7.7E-09	38%	6.8E-09	21%	6.9E-09	23%
dens	6.7E-01	-1.5E-03	**5.6E-09**	6.9E-09	23%	6.9E-09	23%	6.9E-09	23%
veg_amt	-5.7E-01	4.8E-06	**4.1E-09**	-	-	-	-	-	-
veg_wat	-5.6E-01	1.6E-03	**4.0E-09**	4.0E-09	-1%	4.0E-09	1%	4.0E-09	0%
Particulate matter (PM)									
paper_rec	1.1E+00	-9.5E-03	**1.6E-07**	1.6E-07	-3%	1.6E-07	0%	1.6E-07	0%
paper_seg	8.5E-01	-1.1E-04	**9.7E-08**	9.4E-08	-3%	9.8E-08	1%	9.7E-08	0%
elec_rec	3.2E-01	-9.5E-03	**1.4E-08**	1.4E-08	2%	1.4E-08	1%	1.4E-08	-1%
veg_amt	-3.2E-01	8.9E-06	**1.4E-08**	-	-	-	-	-	-
veg_wat	-2.1E-01	2.0E-03	**5.7E-09**	5.9E-09	3%	5.7E-09	-1%	5.8E-09	1%
new_amt	2.0E-01	-2.1E-05	**5.7E-09**	-	-	-	-	-	-
adv_amt	2.0E-01	-2.1E-05	**5.5E-09**	-	-	-	-	-	-
marg_pap	-1.9E-01	3.5E-03	**4.9E-09**	5.4E-09	10%	4.8E-09	-3%	4.9E-09	-1%
glass_rec	1.7E-01	-1.4E-03	**3.9E-09**	4.0E-09	1%	4.0E-09	2%	3.9E-09	0%

Table S15. (continues) Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters and selected impact categories for scenario 3. The sampled uncertainty results from increasing number of Monte Carlo runs (N)

SCENARIO 3

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo					
				$N=10^3$		$N=10^4$		$N=10^5$	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Ionizing radiation (IR)									
paper_rec	1.4E+00	-5.7E-04	**5.6E-10**	5.5E-10	-2%	5.7E-10	0%	5.6E-10	0%
paper_seg	1.0E+00	-5.9E-06	**2.9E-10**	3.2E-10	8%	3.0E-10	2%	2.9E-10	0%
veg_amt	-3.9E-01	4.9E-07	**4.2E-11**	-	-	-	-	-	-
new_amt	2.5E-01	-1.2E-06	**1.7E-11**	-	-	-	-	-	-
adv_amt	2.4E-01	-1.2E-06	**1.7E-11**	-	-	-	-	-	-
veg_wat	-2.3E-01	1.0E-04	**1.5E-11**	1.5E-11	0%	1.5E-11	1%	1.5E-11	0%
elec_rec	1.7E-01	-2.3E-04	**8.5E-12**	8.7E-12	2%	8.6E-12	1%	8.5E-12	0%
oth_amt	1.6E-01	-1.2E-06	**6.9E-12**	-	-	-	-	-	-
marg_pap	-1.0E-01	8.5E-05	**2.9E-12**	2.7E-12	-8%	2.9E-12	2%	2.9E-12	1%
ani_amt	-9.7E-02	4.0E-07	**2.7E-12**	-	-	-	-	-	-
dia_amt	-7.6E-02	5.6E-07	**1.6E-12**	-	-	-	-	-	-
veg_bio	6.9E-02	-4.9E-05	**1.3E-12**	1.3E-12	-1%	1.4E-12	3%	1.3E-12	1%
Photochemical ozone formation (POFP)									
veg_wat	-1.2E+00	-1.0E-02	1.47648E-07	1.4E-07	-2%	1.5E-07	0%	1.5E-07	0%
veg_bio	3.4E-01	4.8E-03	**1.3E-08**	1.2E-08	-6%	1.4E-08	3%	1.3E-08	0%
glass_rec	-3.3E-01	-2.5E-03	**1.2E-08**	1.1E-08	-7%	1.2E-08	0%	1.2E-08	0%
met_gas_1	2.9E-01	2.1E-05	**9.3E-09**	9.6E-09	3%	9.4E-09	0%	9.4E-09	1%
ani_wat	-2.8E-01	-3.2E-03	**8.5E-09**	8.3E-09	-2%	8.3E-09	-2%	8.4E-09	-1%
nox_pap	2.5E-01	2.3E+00	**7.1E-09**	6.9E-09	-2%	7.2E-09	1%	7.1E-09	0%
Terrestrial acidification (TA)									
glass_rec	1.2E+00	-7.2E-03	**1.0E-07**	1.1E-07	3%	1.0E-07	2%	1.0E-07	0%
glass_seg	9.1E-01	-6.9E-05	**6.2E-08**	6.3E-08	3%	6.3E-08	2%	6.2E-08	0%
paper_rec	8.8E-01	-5.7E-03	**5.8E-08**	6.2E-08	8%	5.7E-08	-2%	5.8E-08	0%
heat_rec	5.3E-01	-4.8E-03	**2.1E-08**	2.0E-08	-4%	2.1E-08	1%	2.1E-08	0%
elec_rec	3.8E-01	-8.3E-03	**1.1E-08**	1.0E-08	-7%	1.1E-08	0%	1.1E-08	0%
nox_pap	-2.6E-01	1.9E+00	**5.0E-09**	5.2E-09	3%	5.0E-09	-1%	5.0E-09	0%
Terrestrial eutrophication (TE)									
veg_wat	-9.6E-01	-8.4E-03	1.0E-07	1.06E-07	1%	1.1E-07	0%	1.1E-07	0%
glass_rec	-7.0E-01	-5.3E-03	**5.6E-08**	5.9E-08	5%	5.5E-08	-1%	5.6E-08	0%
nox_pap	5.3E-01	4.8E+00	**3.1E-08**	3.1E-08	-2%	3.1E-08	0%	3.1E-08	0%
paper_seg	5.2E-01	6.0E-05	**3.0E-08**	2.9E-08	-4%	3.0E-08	-1%	3.0E-08	1%
heat_rec	-4.8E-01	-5.4E-03	**2.6E-08**	2.7E-08	4%	2.6E-08	0%	2.6E-08	0%
glass_seg	-4.5E-01	-4.2E-05	**2.3E-08**	2.3E-08	0%	2.3E-08	1%	2.3E-08	0%
Freshwater eutrophication (FE)									
inf	2.5E+00	3.5E-06	**2.8E-09**	2.6E-09	-5%	2.8E-09	0%	2.8E-09	1%
height	-2.3E+00	-9.6E-05	**2.3E-09**	2.5E-09	9%	2.8E-09	20%	2.8E-09	23%
dens	-2.3E+00	-9.6E-04	**2.3E-09**	2.9E-09	27%	2.9E-09	25%	2.8E-09	22%
glass_rec	-1.5E+00	-6.9E-04	**9.5E-10**	9.9E-10	5%	9.2E-10	-2%	9.5E-10	0%
glass_seg	-1.5E+00	-8.5E-06	**9.4E-10**	9.3E-10	-1%	9.3E-10	-2%	9.4E-10	-1%
veg_wat	5.7E-01	3.1E-04	**1.4E-10**	1.6E-10	8%	1.4E-10	-1%	1.5E-10	1%

Table S15. Sensitivity ratio (SR), sensitivity coefficient (SC), analytical uncertainty and sampled uncertainty for selected highly sensitive parameters and selected impact categories for scenario 3. The sampled uncertainty results from increasing number of Monte Carlo runs (N)

SCENARIO 3

Parameter name	SR	SC	Variance						
			Analytical	Monte Carlo N=10^3		N=10^4		N=10^5	
[unit]	[-]	[PE/unit]	**[PE^2]**	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical	[PE^2]	Difference from analytical
Marine eutrophication (ME)									
inf	9.8E-01	9.7E-04	**2.1E-04**	2.1E-04	-2%	2.1E-04	-2%	2.1E-04	0%
height	-8.9E-01	-2.7E-02	**1.8E-04**	2.0E-04	11%	2.2E-04	27%	2.2E-04	23%
dens	-8.9E-01	-2.7E-01	**1.8E-04**	2.2E-04	22%	2.2E-04	23%	2.2E-04	23%
veg_wat	2.0E-01	7.6E-02	**8.6E-06**	8.3E-06	-3%	8.7E-06	2%	8.7E-06	1%
lossVS	-1.7E-01	-2.7E-02	**6.3E-06**	6.6E-06	5%	6.2E-06	-2%	6.3E-06	0%
veg_bio	-5.9E-02	-3.7E-02	**7.7E-07**	8.1E-07	5%	7.9E-07	2%	7.8E-07	1%
Freshwater ecotoxicity (ET)									
inf	7.2E+00	2.6E-04	**1.5E-05**	1.5E-05	1%	1.5E-05	-1%	1.5E-05	1%
height	-6.5E+00	-7.0E-03	**1.2E-05**	1.4E-05	16%	1.5E-05	23%	1.4E-05	18%
dens	-6.5E+00	-7.0E-02	**1.2E-05**	1.4E-05	18%	1.5E-05	25%	1.5E-05	21%
paper_rec	-6.1E+00	-7.8E-02	**1.1E-05**	9.8E-06	-9%	1.1E-05	-1%	1.1E-05	0%
paper_seg	-6.1E+00	-1.1E-03	**1.1E-05**	1.1E-05	1%	1.1E-05	1%	1.1E-05	0%
veg_amt	2.7E+00	1.1E-04	**2.1E-06**	-	-	-	-	-	-
new_amt	-1.8E+00	-2.7E-04	**9.2E-07**	-	-	-	-	-	-
adv_amt	-1.8E+00	-2.7E-04	**8.9E-07**	-	-	-	-	-	-
veg_wat	1.7E+00	2.3E-02	**7.9E-07**	7.8E-07	-2%	7.8E-07	-2%	7.8E-07	-2%
Resource depletion, fossil (Rdfos)									
paper_rec	1.1E+01	-6.6E-02	**7.6E-06**	7.8E-06	2%	7.7E-06	1%	7.6E-06	0%
paper_seg	6.4E+00	-5.4E-04	**2.4E-06**	2.4E-06	-3%	2.4E-06	-1%	2.4E-06	-1%
veg_wat	-4.5E+00	2.8E-02	**1.2E-06**	1.3E-06	6%	1.2E-06	-2%	1.2E-06	0%
tr_pap_d	-3.6E+00	5.8E-04	**7.6E-07**	8.1E-07	7%	7.4E-07	-3%	7.7E-07	1%
coll_res	-3.6E+00	5.3E-03	**7.4E-07**	7.2E-07	-3%	7.6E-07	2%	7.5E-07	1%
elec_rec	3.4E+00	-6.6E-02	**6.8E-07**	6.3E-07	-7%	6.8E-07	-1%	6.7E-07	-1%
Resource depletion (RD)									
veg_amt	6.4E-02	8.0E-11	1.1E-18	-	-	-	-	-	-
new_amt	-3.6E-02	-1.7E-10	**3.6E-19**	-	-	-	-	-	-
adv_amt	-3.6E-02	-1.7E-10	**3.6E-19**	-	-	-	-	-	-
ani_amt	2.1E-02	8.6E-11	**1.2E-19**	-	-	-	-	-	-
oth_amt	-1.2E-02	-9.1E-11	**4.0E-20**	-	-	-	-	-	-
dia_amt	1.2E-02	8.8E-11	**4.0E-20**	-	-	-	-	-	-
pap_amt	1.2E-02	9.5E-11	**4.0E-20**	-	-	-	-	-	-
pla_amt	9.1E-03	9.2E-11	**2.3E-20**	-	-	-	-	-	-
yar_amt	9.1E-03	9.0E-11	**2.3E-20**	-	-	-	-	-	-
dir_amt	6.1E-03	7.9E-11	**1.0E-20**	-	-	-	-	-	-
paper_rec	-3.1E-06	-1.2E-12	**2.6E-27**	2.6E-27	-2%	2.6E-27	0%	2.6E-27	0%
paper_seg	-2.0E-06	-1.1E-14	**1.1E-27**	1.1E-27	-4%	1.1E-27	1%	1.1E-27	1%
veg_wat	5.9E-07	2.5E-13	**9.5E-29**	9.2E-29	-4%	9.7E-29	2%	9.6E-29	0%
elec_rec	-4.4E-07	-5.8E-13	**5.3E-29**	5.3E-29	0%	5.5E-29	3%	5.4E-29	1%
glass_seg	4.3E-07	2.0E-15	**5.0E-29**	5.8E-29	16%	5.1E-29	1%	5.1E-29	1%
tr_pap_d	3.47E-07	3.81E-15	**3.3E-29**	3.10E-29	-5%	3.43E-29	5%	3.32E-29	2%

SI.5 Uncertainty analysis: complete parameters´ sets

Tables S16 – S18 provide the uncertainty analysis results for complete parameters´ sets for all impact categories and waste management scenarios. The tables report the normalized result scores, in order to compare them with the analytically calculated variance via the coefficient of variation (CV). The same is carried out with results from the Monte Carlo sampling for an increasing number of runs. Means, variances and CVs are calculated with respect to the corresponding N.

Table S16. Variance obtained by analytical and sampling propagation for scenario 1. The Monte Carlo results are obtained for a different number of sampling points (N)

		Scenario 1													
		GWP	**ODP**	**HTc**	**HTnc**	**PM**	**IR**	**POFP**	**TA**	**TE**	**FE**	**ME**	**ET**	**RDfos**	**RD**
Normalized result score [PE]		-9.09E-02	-6.58E-05	1.21E-03	-7.37E-04	-2.09E-02	-5.41E-03	-5.88E-03	-3.24E-02	-8.22E-03	-6.33E-04	-9.58E-03	-4.58E-02	-7.85E-02	-1.90E-05
Analytical variance [PE^2]		**2.25E-05**	**1.01E-11**	**2.41E-09**	**1.29E-07**	**1.13E-06**	**6.70E-08**	**1.32E-06**	**3.45E-06**	**5.26E-06**	**1.91E-09**	**6.55E-06**	**2.23E-05**	**4.18E-05**	**1.34E-12**
Coefficient of variation [%]		-5.2%	-4.8%	4.1%	-48.7%	-5.1%	-4.8%	-19.6%	-5.7%	-27.9%	-6.9%	-26.7%	-10.3%	-8.2%	-6.1%
Monte Carlo simulation															
Mean from Monte Carlo sample [PE]	$N=10^3$	-9.08E-02	-6.59E-05	1.21E-03	-7.31E-04	-2.09E-02	-5.41E-03	-5.89E-03	-3.24E-02	-8.25E-03	-6.34E-04	-9.61E-03	-4.57E-02	-7.82E-02	-1.89E-05
	$N=10^4$	-9.10E-02	-6.58E-05	1.21E-03	-7.37E-04	-2.09E-02	-5.41E-03	-5.88E-03	-3.24E-02	-8.21E-03	-6.34E-04	-9.58E-03	-4.57E-02	-7.84E-02	-1.90E-05
	$N=10^5$	-9.09E-02	-6.58E-05	1.21E-03	-7.33E-04	-2.09E-02	-5.41E-03	-5.88E-03	-3.24E-02	-8.22E-03	-6.34E-04	-9.57E-03	-4.58E-02	-7.85E-02	-1.90E-05
Sampled variance [PE^2]	$N=10^3$	**2.38E-05**	**1.00E-11**	**2.53E-09**	**1.34E-07**	**1.08E-06**	**6.60E-08**	**1.15E-06**	**2.97E-06**	**4.59E-06**	**1.87E-09**	**5.72E-06**	**2.27E-05**	**4.07E-05**	**1.32E-12**
	$N=10^4$	**2.22E-05**	**1.00E-11**	**2.31E-09**	**1.21E-07**	**1.04E-06**	**6.66E-08**	**1.19E-06**	**2.99E-06**	**4.94E-06**	**1.95E-09**	**5.86E-06**	**2.25E-05**	**3.73E-05**	**1.36E-12**
	$N=10^5$	**2.22E-05**	**1.02E-11**	**2.34E-09**	**1.21E-07**	**1.03E-06**	**6.67E-08**	**1.21E-06**	**3.02E-06**	**4.77E-06**	**1.91E-09**	**6.04E-06**	**2.22E-05**	**3.90E-05**	**1.33E-12**
Difference of sampled mean from normalized result [%]	$N=10^3$	-0.1%	0.1%	0.1%	-0.8%	0.0%	0.1%	0.2%	0.0%	0.4%	0.2%	0.3%	-0.1%	-0.3%	-0.3%
	$N=10^4$	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	-0.1%	-0.1%	0.1%	0.1%	-0.2%	-0.1%	0.0%
	$N=10^5$	0.0%	0.1%	0.0%	-0.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	-0.1%	0.0%	0.0%	0.0%
Difference of sampled variance from calculated variance [%]	$N=10^3$	**5.7%**	**1.2%**	**5.0%**	**4.0%**	**4.6%**	**1.6%**	**13.2%**	**14.0%**	**12.7%**	**1.7%**	**12.6%**	**1.8%**	**2.7%**	**1.4%**
	$N=10^4$	**1.2%**	**1.0%**	**4.2%**	**6.0%**	**8.3%**	**0.6%**	**10.4%**	**13.5%**	**6.0%**	**2.3%**	**10.4%**	**0.9%**	**10.8%**	**1.7%**
	$N=10^5$	**1.4%**	**0.9%**	**2.9%**	**5.5%**	**8.9%**	**0.5%**	**8.2%**	**12.7%**	**9.2%**	**0.0%**	**7.7%**	**0.3%**	**6.7%**	**0.3%**
Coefficient of variation [%]	$N=10^3$	-5.4%	-4.8%	4.2%	-50.0%	-5.0%	-4.7%	-18.2%	-5.3%	-26.0%	-6.8%	-24.9%	-10.4%	-8.2%	-6.1%
	$N=10^4$	-5.2%	-4.8%	4.0%	-47.1%	-4.9%	-4.8%	-18.5%	-5.3%	-27.1%	-7.0%	-25.3%	-10.4%	-7.8%	-6.1%
	$N=10^5$	-5.2%	-4.9%	4.0%	-47.5%	-4.9%	-4.8%	-18.7%	-5.4%	-26.6%	-6.9%	-25.7%	-10.3%	-8.0%	-6.1%

Table S17. Variance obtained by analytical and sampling propagation for scenario 2. The Monte Carlo results are obtained for a different number of sampling points (N)

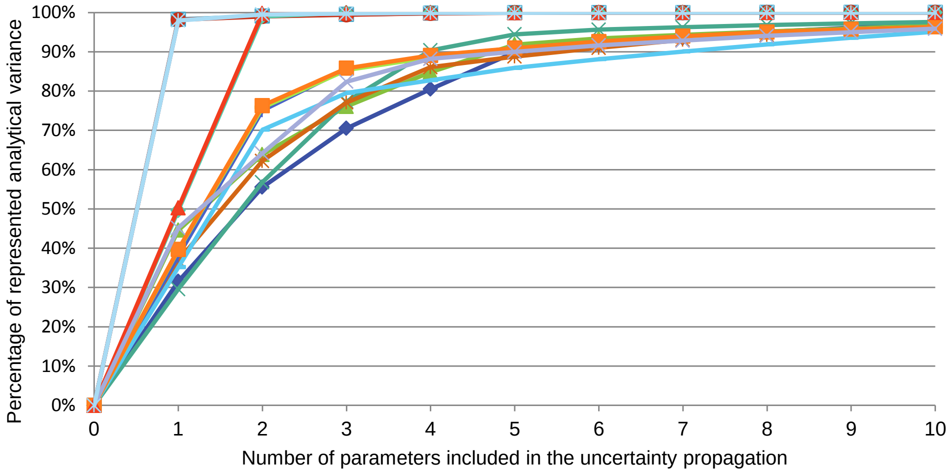
		Scenario 2													
		GWP	**ODP**	**HTc**	**HTnc**	**PM**	**IR**	**POFP**	**TA**	**TE**	**FE**	**ME**	**ET**	**RDfos**	**RD**
Normalized result score [PE]		-8.45E-02	-6.68E-05	3.88E-03	2.13E-01	-2.12E-02	-5.48E-03	-7.31E-03	-3.23E-02	-1.09E-02	-3.08E-03	1.58E-02	1.69E-01	-6.36E-02	-1.69E-05
Analytical variance [PE^2]		**1.64E-05**	**1.01E-11**	**2.70E-08**	**1.61E-04**	**7.90E-07**	**6.67E-08**	**7.30E-07**	**2.00E-06**	**2.87E-06**	**4.99E-08**	**6.55E-06**	**2.04E-04**	**3.07E-05**	**1.02E-12**
Coefficient of variation [%]		-4.8%	-4.8%	4.2%	6.0%	-4.2%	-4.7%	-11.7%	-4.4%	-15.6%	-7.2%	16.2%	8.5%	-8.7%	-6.0%
Monte Carlo simulation															
Mean from Monte Carlo sample [PE]	$N=10^3$	-8.45E-02	-6.68E-05	3.88E-03	2.13E-01	-2.12E-02	-5.48E-03	-7.32E-03	-3.23E-02	-1.09E-02	-3.08E-03	1.57E-02	1.68E-01	-6.38E-02	-1.69E-05
	$N=10^4$	-8.44E-02	-6.68E-05	3.89E-03	2.13E-01	-2.12E-02	-5.48E-03	-7.31E-03	-3.23E-02	-1.09E-02	-3.08E-03	1.58E-02	1.68E-01	-6.36E-02	-1.69E-05
	$N=10^5$	-8.45E-02	-6.68E-05	3.88E-03	2.13E-01	-2.12E-02	-5.48E-03	-7.30E-03	-3.23E-02	-1.09E-02	-3.08E-03	1.58E-02	1.68E-01	-6.36E-02	-1.69E-05
Sampled variance [PE^2]	$N=10^3$	**1.71E-05**	**9.47E-12**	**2.71E-08**	**1.62E-04**	**7.88E-07**	**6.23E-08**	**7.55E-07**	**2.05E-06**	**2.97E-06**	**4.97E-08**	**6.64E-06**	**2.01E-04**	**3.02E-05**	**9.42E-13**
	$N=10^4$	**1.70E-05**	**1.04E-11**	**2.72E-08**	**1.63E-04**	**7.75E-07**	**6.57E-08**	**7.26E-07**	**2.04E-06**	**2.81E-06**	**4.93E-08**	**6.53E-06**	**2.08E-04**	**3.04E-05**	**1.04E-12**
	$N=10^5$	**1.68E-05**	**1.01E-11**	**2.70E-08**	**1.61E-04**	**7.93E-07**	**6.71E-08**	**7.32E-07**	**2.02E-06**	**2.87E-06**	**5.00E-08**	**6.61E-06**	**2.06E-04**	**3.07E-05**	**1.03E-12**
Difference of sampled mean from normalized result [%]	$N=10^3$	0.0%	0.1%	-0.1%	-0.1%	0.1%	0.1%	0.2%	0.1%	0.3%	-0.1%	-0.3%	-0.1%	0.3%	0.1%
	$N=10^4$	-0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	-0.1%	0.0%	0.0%
	$N=10^5$	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.2%	-0.3%	0.1%	-0.1%
Difference of sampled variance from calculated variance [%]	$N=10^3$	**3.7%**	**6.4%**	**0.5%**	**0.8%**	**0.2%**	**6.5%**	**3.4%**	**2.7%**	**3.5%**	**0.5%**	**1.4%**	**1.5%**	**1.8%**	**7.7%**
	$N=10^4$	**3.4%**	**2.9%**	**0.6%**	**1.0%**	**1.9%**	**1.5%**	**0.6%**	**2.2%**	**2.1%**	**1.2%**	**0.2%**	**2.2%**	**1.2%**	**1.7%**
	$N=10^5$	**2.3%**	**0.3%**	**0.2%**	**0.0%**	**0.5%**	**0.7%**	**0.3%**	**1.1%**	**0.0%**	**0.1%**	**0.9%**	**0.9%**	**0.0%**	**0.5%**
Coefficient of variation [%]	$N=10^3$	-4.9%	-4.6%	4.2%	6.0%	-4.2%	-4.6%	-11.9%	-4.4%	-15.8%	-7.2%	16.4%	8.4%	-8.6%	-5.7%
	$N=10^4$	-4.9%	-4.8%	4.2%	6.0%	-4.2%	-4.7%	-11.7%	-4.4%	-15.4%	-7.2%	16.2%	8.6%	-8.7%	-6.0%
	$N=10^5$	-4.9%	-4.8%	4.2%	6.0%	-4.2%	-4.7%	-11.7%	-4.4%	-15.6%	-7.2%	16.3%	8.5%	-8.7%	-6.0%

Table S18. Variance obtained by analytical and sampling propagation for scenario 3. The Monte Carlo results are obtained for a different number of sampling points (N)

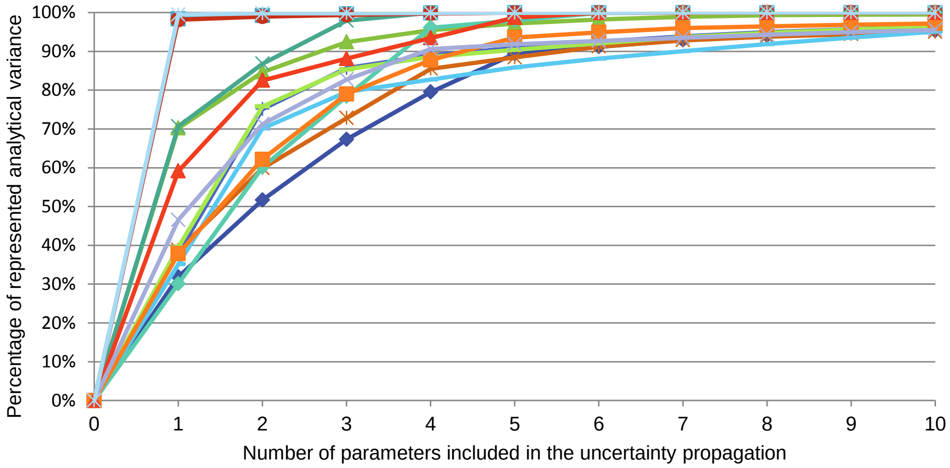
Scenario 3															
		GWP	**ODP**	**HTc**	**HTnc**	**PM**	**IR**	**POFP**	**TA**	**TE**	**FE**	**ME**	**ET**	**RDfos**	**RD**
Normalized result score [PE]		-1.76E-02	8.14E-04	1.18E-02	-2.24E-03	-7.36E-03	-3.34E-04	6.68E-03	-5.45E-03	6.72E-03	4.22E-04	2.98E-01	1.07E-02	-4.84E-03	3.29E-07
Analytical variance [PE^2]		1.95E-05	3.09E-09	1.01E-06	8.66E-08	2.90E-07	8.90E-10	2.31E-07	2.68E-07	3.11E-07	9.53E-09	5.82E-04	6.20E-05	1.47E-05	4.04E-27
Coefficient of variation [%]		-25.1%	6.8%	8.5%	-13.1%	-7.3%	-8.9%	7.2%	-9.5%	8.3%	23.1%	8.1%	73.6%	-79.1%	0.0%
Monte Carlo simulation															
Mean from Monte Carlo sample [PE]	$N=10^3$	-1.75E-02	8.15E-04	1.19E-02	-2.24E-03	-7.37E-03	-3.35E-04	6.68E-03	-5.47E-03	6.72E-03	4.27E-04	3.00E-01	1.11E-02	-4.94E-03	3.29E-07
	$N=10^4$	-1.76E-02	8.13E-04	1.19E-02	-2.23E-03	-7.36E-03	-3.34E-04	6.70E-03	-5.42E-03	6.73E-03	4.28E-04	3.00E-01	1.09E-02	-4.84E-03	3.29E-07
	$N=10^5$	-1.75E-02	8.14E-04	1.19E-02	-2.23E-03	-7.36E-03	-3.34E-04	6.68E-03	-5.45E-03	6.72E-03	4.27E-04	3.00E-01	1.11E-02	-4.85E-03	3.29E-07
Sampled variance [PE^2]	$N=10^3$	1.96E-05	2.95E-09	1.22E-06	9.28E-08	3.12E-07	9.56E-10	2.22E-07	2.76E-07	3.07E-07	1.11E-08	6.98E-04	6.96E-05	1.51E-05	4.33E-27
	$N=10^4$	1.95E-05	3.21E-09	1.16E-06	9.32E-08	2.96E-07	8.84E-10	2.28E-07	2.75E-07	3.07E-07	1.08E-08	6.66E-04	6.67E-05	1.36E-05	4.02E-27
	$N=10^5$	1.95E-05	3.09E-09	1.16E-06	9.00E-08	2.88E-07	8.91E-10	2.34E-07	2.69E-07	3.11E-07	1.08E-08	6.75E-04	6.84E-05	1.39E-05	4.03E-27
Difference of sampled mean from normalized result [%]	$N=10^3$	-0.1%	0.1%	0.6%	-0.3%	0.1%	0.1%	0.1%	0.3%	0.0%	1.2%	0.6%	4.1%	1.9%	0.0%
	$N=10^4$	0.3%	-0.1%	0.6%	-0.5%	-0.1%	-0.1%	0.4%	-0.5%	0.2%	1.3%	0.7%	1.9%	-0.1%	0.0%
	$N=10^5$	-0.1%	0.0%	4.98E-03	-3.81E-03	0.0%	-2.21E-04	0.0%	-0.1%	0.0%	1.2%	0.5%	3.96E-02	1.08E-03	0.0%
Difference of sampled variance from calculated variance [%]	$N=10^3$	0.7%	4.6%	20.4%	7.2%	7.3%	7.3%	4.0%	2.9%	1.4%	16.2%	20.0%	12.2%	2.7%	7.2%
	$N=10^4$	0.0%	3.7%	15.2%	7.6%	1.7%	0.7%	1.3%	2.6%	1.3%	13.2%	14.6%	7.5%	7.6%	0.6%
	$N=10^5$	0.1%	0.2%	1.48E-01	3.98E-02	0.8%	6.35E-04	1.3%	0.4%	0.0%	12.8%	16.0%	1.02E-01	5.5%	0.4%
Coefficient of variation [%]	$N=10^3$	-25.3%	6.7%	9.3%	-13.6%	-7.6%	-9.2%	7.0%	-9.6%	8.2%	24.6%	8.8%	74.9%	-78.7%	0.0%
	$N=10^4$	-25.1%	7.0%	9.1%	-13.7%	-7.4%	-8.9%	7.1%	-9.7%	8.2%	24.3%	8.6%	74.9%	-76.1%	0.0%
	$N=10^5$	-25.1%	6.8%	9.06E-02	-1.34E-01	-7.3%	-8.93E-02	7.2%	-9.5%	8.3%	24.3%	8.7%	7.43E-01	-7.69E-01	0.0%

SI. 5 Global Sensitivity Analysis perspective: theoretical

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

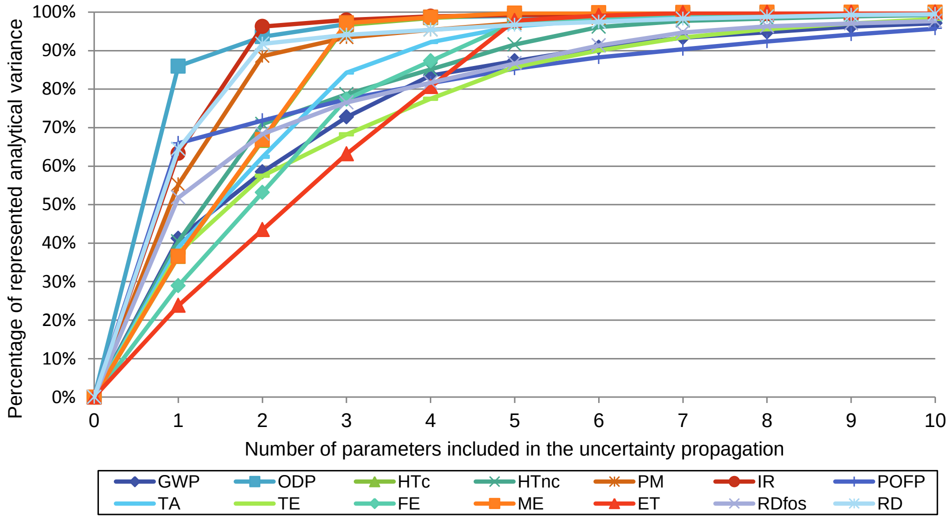


Figure S12. Percentage of the total uncertainty in the scenario obtained grouping hierarchically the parameters according to their importance in the model.

Table S.19 Parameters included in the uncertainty propagation and associated percentage of represented analytical variance for scenario 1. Grey cells indicate the set of parameters that are required to reach 90% of represented uncertainty

Scenario 1

Number of parameters included in the uncertainty propagation

Parameter (*percentage of represented analytical variance*)

Impact category	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
GWP	elec_rec *32%*	veg_wat *56%*	paper_rec *71%*	heat_rec *81%*	paper_seg *90%*	ani_wat *92%*	veg_ene *94%*	pla_ene *95%*	pla_fos *96%*	ani_ene *97%*
ODP	alu_rec *98%*	paper_rec *99%*	paper_seg *99%*	elec_rec *100%*	veg_wat *100%*	ani_wat *100%*	veg_ene *100%*	pla_ene *100%*	marg_pap *100%*	ani_ene *100%*
HTc	elec_rec *45%*	paper_rec *64%*	paper_seg *76%*	veg_wat *85%*	alu_rec *92%*	gravel_rec *93%*	veg_ene *94%*	pla_ene *95%*	glass_rec *96%*	steel_rec *97%*
HTnc	elec_rec *30%*	paper_rec *57%*	paper_seg *77%*	veg_wat *90%*	alu_rec *94%*	ani_wat *96%*	veg_ene *96%*	pla_ene *97%*	steel_rec *97%*	glass_rec *98%*
PM	elec_rec *37%*	veg_wat *62%*	paper_rec *77%*	paper_seg *86%*	nox_inc *89%*	heat_rec *91%*	ani_wat *93%*	alu_rec *94%*	pla_ene *96%*	veg_ene *96%*
IR	alu_rec *98%*	paper_rec *99%*	paper_seg *99%*	elec_rec *100%*	veg_wat *100%*	gravel_rec *100%*	ani_wat *100%*	veg_ene *100%*	pla_ene *100%*	ani_ene *100%*
POFP	nox_inc *38%*	heat_rec *75%*	veg_wat *86%*	elec_rec *89%*	ani_wat *91%*	veg_ene *93%*	pla_ene *94%*	glass_rec *95%*	ani_ene *96%*	nox_pap *96%*
TA	heat_rec *35%*	veg_wat *70%*	elec_rec *80%*	nox_inc *83%*	glass_rec *86%*	ani_wat *88%*	alu_rec *90%*	glass_seg *92%*	paper_rec *94%*	veg_ene *95%*
TE	nox_inc *39%*	heat_rec *76%*	veg_wat *85%*	elec_rec *89%*	ani_wat *90%*	veg_ene *92%*	pla_ene *94%*	glass_rec *95%*	ani_ene *96%*	nox_pap *96%*
FE	glass_rec *50%*	glass_seg *99%*	paper_rec *100%*	paper_seg *100%*	gravel_rec *100%*	elec_rec *100%*	alu_rec *100%*	coll_res *100%*	veg_wat *100%*	tr_res_d *100%*
ME	nox_inc *40%*	heat_rec *76%*	veg_wat *86%*	elec_rec *89%*	ani_wat *91%*	veg_ene *93%*	pla_ene *94%*	glass_rec *95%*	ani_ene *96%*	nox_pap *96%*
ET	paper_rec *50%*	paper_seg *100%*	alu_rec *100%*	elec_rec *100%*	glass_rec *100%*	glass_seg *100%*	zinc_iron *100%*	pla_wat *100%*	veg_wat *100%*	coll_res *100%*
RDfos	elec_rec *45%*	veg_wat *64%*	paper_rec *82%*	paper_seg *88%*	coll_res *90%*	ani_wat *92%*	tr_res_d *93%*	tr_res_f *94%*	veg_ene *95%*	pla_ene *96%*
RD	gravel_rec *98%*	veg_wat *100%*	ani_wat *100%*	yar_wat *100%*	dia_wat *100%*	pap_wat *100%*	adv_wat *100%*	pla_wat *100%*	dir_wat *100%*	new_wat *100%*

Table S.20 Parameters included in the uncertainty propagation and associated percentage of represented analytical variance for scenario 2. Grey cells indicate the set of parameters that are required to reach 90% of represented uncertainty

Scenario 2

Number of parameters included in the uncertainty propagation

Parameter (*percentage of represented analytical variance*)

Impact category										
GWP	elec_rec *32%*	paper_rec *52%*	veg_wat *67%*	paper_seg *79%*	heat_rec *89%*	pla_ene *91%*	pla_fos *93%*	ani_wat *94%*	marg_pap *95%*	gas_burn *95%*
ODP	alu_rec *98%*	paper_rec *99%*	paper_seg *100%*	elec_rec *100%*	veg_wat *100%*	pla_ene *100%*	ani_wat *100%*	marg_pap *100%*	bio_yield *100%*	elec_dig *100%*
HTc	pret_dig *70%*	yar_wat *85%*	veg_wat *92%*	elec_rec *95%*	paper_rec *97%*	paper_seg *98%*	alu_rec *99%*	ani_wat *99%*	gravel_rec *99%*	pla_ene *100%*
HTnc	pret_dig *71%*	veg_wat *87%*	yar_wat *98%*	ani_wat *100%*	paper_rec *100%*	elec_rec *100%*	paper_seg *100%*	alu_rec *100%*	pla_ene *100%*	steel_rec *100%*
PM	elec_rec *39%*	paper_rec *60%*	veg_wat *73%*	paper_seg *86%*	nox_inc *88%*	alu_rec *91%*	heat_rec *93%*	pla_ene *94%*	ani_wat *94%*	marg_pap *95%*
IR	alu_rec *98%*	paper_rec *99%*	paper_seg *100%*	elec_rec *100%*	veg_wat *100%*	gravel_rec *100%*	pla_ene *100%*	ani_wat *100%*	marg_pap *100%*	bio_yield *100%*
POFP	heat_rec *51%*	nox_inc *70%*	veg_wat *84%*	elec_rec *87%*	pla_ene *90%*	glass_rec *91%*	ani_wat *92%*	glass_seg *93%*	dia_ene *94%*	paper_seg *94%*
TA	heat_rec *45%*	veg_wat *62%*	elec_rec *74%*	nox_inc *80%*	glass_rec *83%*	alu_rec *87%*	glass_seg *90%*	paper_rec *93%*	pla_ene *94%*	ani_wat *95%*
TE	heat_rec *54%*	nox_inc *71%*	veg_wat *84%*	elec_rec *87%*	pla_ene *90%*	glass_rec *91%*	nox_pap *92%*	paper_seg *93%*	glass_seg *94%*	ani_wat *95%*
FE	P_sub *30%*	pret_dig *60%*	veg_wat *78%*	ani_wat *96%*	glass_rec *98%*	glass_seg *100%*	yar_wat *100%*	paper_rec *100%*	paper_seg *100%*	gravel_rec *100%*
ME	pret_dig *38%*	heat_rec *62%*	nox_inc *79%*	ani_wat *88%*	veg_wat *94%*	elec_rec *95%*	pla_ene *96%*	glass_rec *96%*	nox_pap *97%*	paper_seg *97%*
ET	pret_dig *59%*	veg_wat *83%*	yar_wat *88%*	paper_rec *93%*	paper_seg *99%*	ani_wat *100%*	cop_inc *100%*	P_sub *100%*	alu_rec *100%*	glass_rec *100%*
RDfos	elec_rec *47%*	paper_rec *71%*	veg_wat *83%*	paper_seg *91%*	pla_ene *92%*	coll_res *93%*	ani_wat *94%*	marg_pap *94%*	bio_yield *95%*	elec_dig *96%*
RD	gravel_rec *99%*	veg_wat *100%*	pret_dig *100%*	dia_wat *100%*	ani_wat *100%*	yar_wat *100%*	pap_wat *100%*	adv_wat *100%*	new_wat *100%*	dir_wat *100%*

Table S.21 Parameters included in the uncertainty propagation and associated percentage of represented analytical variance for scenario 3. Grey cells indicate the set of parameters that are required to reach 90% of represented uncertainty

Scenario 3

Number of parameters included in the uncertainty propagation

Parameter (*percentage of represented analytical variance*)

Impact category										
GWP	veg_wat *41%*	paper_rec *58%*	met_gas_1 *73%*	paper_seg *84%*	veg_bio *87%*	met_gas_3 *91%*	met_gas_2 *93%*	ani_wat *95%*	elec_rec *96%*	veg_gas *97%*
ODP	veg_wat *86%*	veg_bio *94%*	ani_wat *97%*	ani_bio *99%*	veg_gas *99%*	pap_bio *99%*	oth_bio *100%*	adv_bio *100%*	dir_bio *100%*	ani_gas *100%*
HTc	inf *36%*	height *67%*	dens *97%*	veg_wat *98%*	lossVS *100%*	veg_bio *100%*	ani_wat *100%*	paper_rec *100%*	ani_bio *100%*	paper_seg *100%*
HTnc	paper_rec *40%*	paper_seg *71%*	inf *79%*	height *85%*	dens *92%*	veg_wat *96%*	elec_rec *98%*	glass_rec *98%*	marg_pap *99%*	veg_bio *99%*
PM	paper_rec *55%*	paper_seg *89%*	elec_rec *93%*	veg_wat *95%*	marg_pap *97%*	glass_rec *98%*	glass_seg *99%*	veg_bio *99%*	heat_rec *99%*	inf *99%*
IR	paper_rec *63%*	paper_seg *96%*	veg_wat *98%*	elec_rec *99%*	marg_pap *99%*	veg_bio *99%*	glass_seg *100%*	ani_wat *100%*	tr_pap_d *100%*	coll_res *100%*
POFP	veg_wat *66%*	veg_bio *72%*	glass_rec *77%*	met_gas_1 *82%*	ani_wat *85%*	nox_pap *88%*	heat_rec *90%*	ani_bio *92%*	glass_seg *94%*	paper_seg *96%*
TA	glass_rec *39%*	glass_seg *62%*	paper_rec *84%*	heat_rec *92%*	elec_rec *96%*	nox_pap *98%*	paper_seg *99%*	marg_pap *100%*	inf *100%*	height *100%*
TE	veg_wat *37%*	glass_rec *57%*	nox_pap *68%*	paper_seg *78%*	heat_rec *86%*	glass_seg *90%*	elec_rec *93%*	veg_bio *96%*	ani_wat *97%*	marg_pap *98%*
FE	inf *29%*	height *53%*	dens *77%*	glass_rec *87%*	glass_seg *97%*	veg_wat *99%*	lossVS *100%*	paper_rec *100%*	veg_bio *100%*	ani_wat *100%*
ME	inf *37%*	height *67%*	dens *97%*	veg_wat *99%*	lossVS *100%*	veg_bio *100%*	ani_wat *100%*	ani_bio *100%*	glass_rec *100%*	nox_pap *100%*
ET	inf *24%*	height *43%*	dens *63%*	paper_rec *81%*	paper_seg *98%*	veg_wat *99%*	lossVS *100%*	veg_bio *100%*	ani_wat *100%*	ani_bio *100%*
RDfos	paper_rec *52%*	paper_seg *68%*	veg_wat *77%*	tr_pap_d *82%*	coll_res *87%*	elec_rec *91%*	tr_res_f *95%*	marg_pap *96%*	veg_bio *97%*	tr_pap_d2 *98%*
RD	paper_rec *64%*	paper_seg *92%*	veg_wat *94%*	elec_rec *95%*	glass_seg *97%*	tr_pap_d *97%*	coll_res *98%*	tr_res_f *99%*	marg_pap *99%*	veg_bio *99%*

SI.6 Global Sensitivity Analysis: results

The following Figures (S13 – S26) illustrate the results of the Monte Carlo sampling that was carried out to verify that the behaviour of additivity of variances was respected also by the sampling method. The red line reports the behaviour of the summed analytical variances according to their hierarchical order for that scenario and impact category, as shown in Figure S8. Moreover, the single uncertainties calculated with the Monte Carlo in section SI.3 are also summed progressively respecting the same order, for increasing N. Lastly, the uncertainty was also sampled progressively enlarging the set of parameters considered in the propagation, with the same order followed by the previous steps and with increasing N. The graphs are all normalized to the total variance for the impact category, and the representativeness on the *y* axis is given as a percentage.

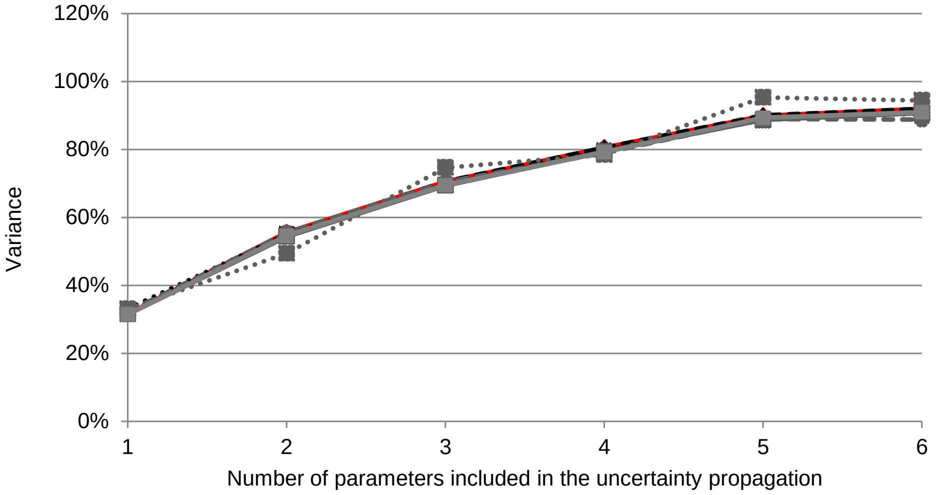
The test allowed validating the fact that the additivity of variances was respected by both methods, and that with a few representative parameters it is possible to quickly reach a high percentage of the total variance for a given impact category and scenario. The Monte Carlo results fit adequately the calculated curve for most cases.

Notable differences between the curves in the graphs correspond to those impact categories that presented high Differences between the two uncertainty propagation methods between the calculations for single parameters in section SI.3. Moreover, when this difference is occurring for a high ranking parameter, the whole resulting curve will be shifted from the behaviour of the Monte Carlo. An example is provided by PM for scenario 1 (Table S13 and Figure S17).

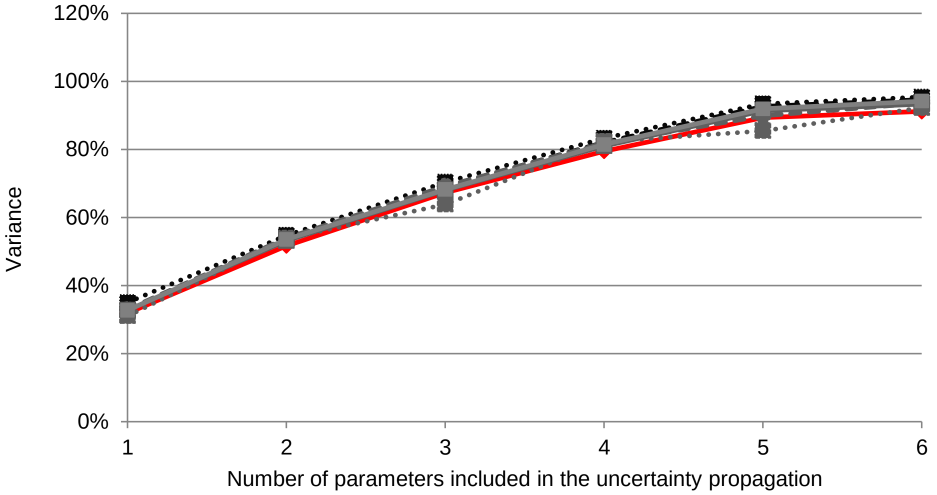
Some impact categories present almost horizontal lines, meaning that only one parameter is sufficient to represent almost all the uncertainty in that impact category. An example is ODP, especially for scenarios 1 and 2 (Figure S14), as well as IR (Figure S18) and RD (Figure S26).

Figure S13. Additivity of variances for analytical (red) and sampling (grey) methods; GWP impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

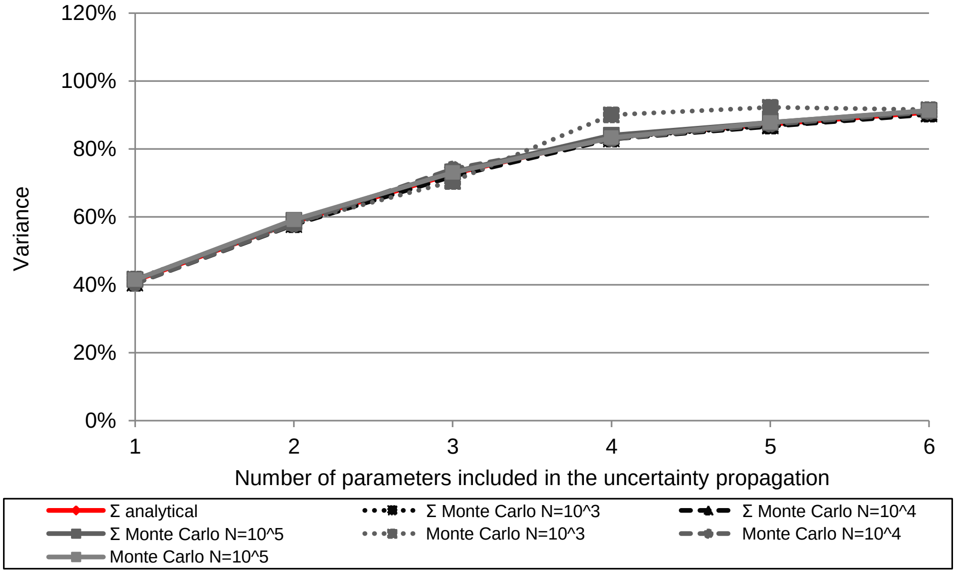
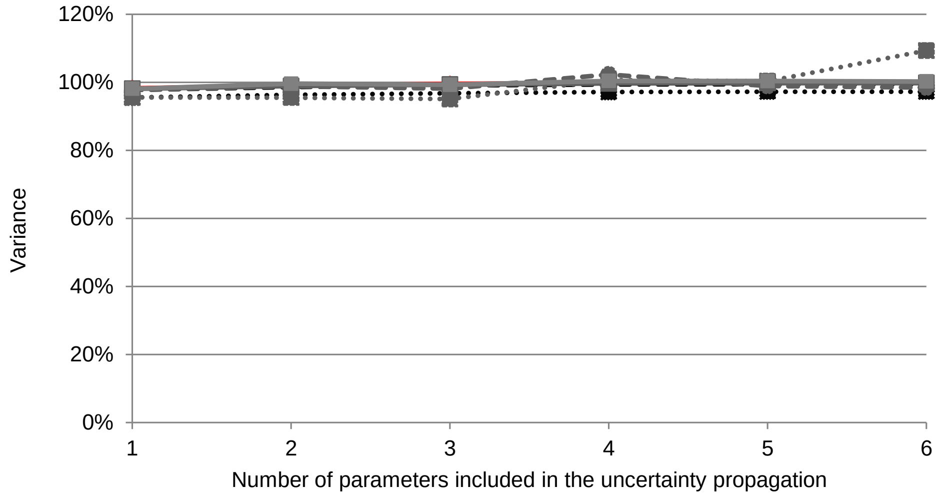
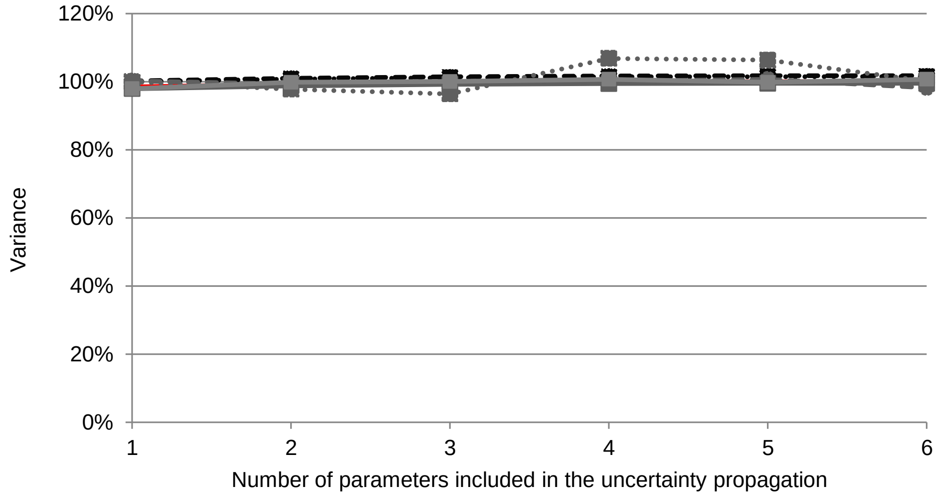


Figure S14. Additivity of variances for analytical (red) and sampling (grey) methods; ODP impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

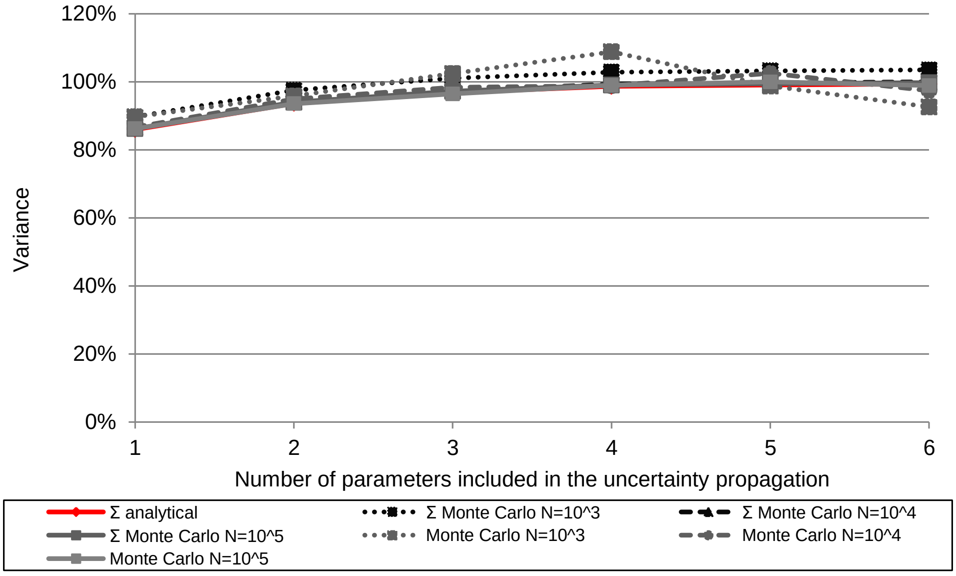
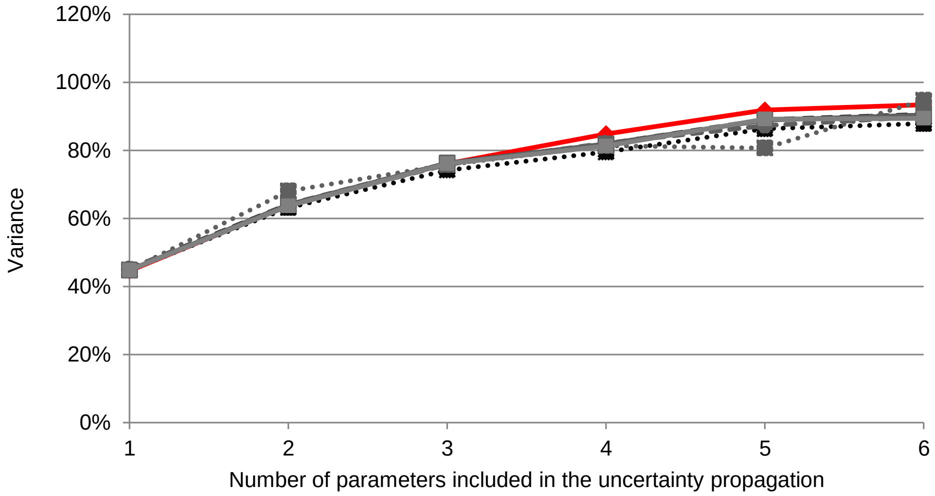
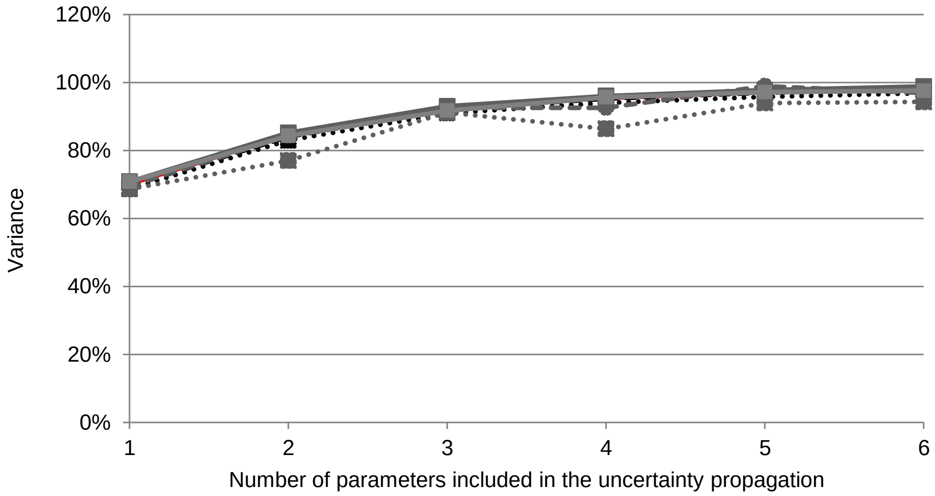


Figure S15. Additivity of variances for analytical (red) and sampling (grey) methods; HTc impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

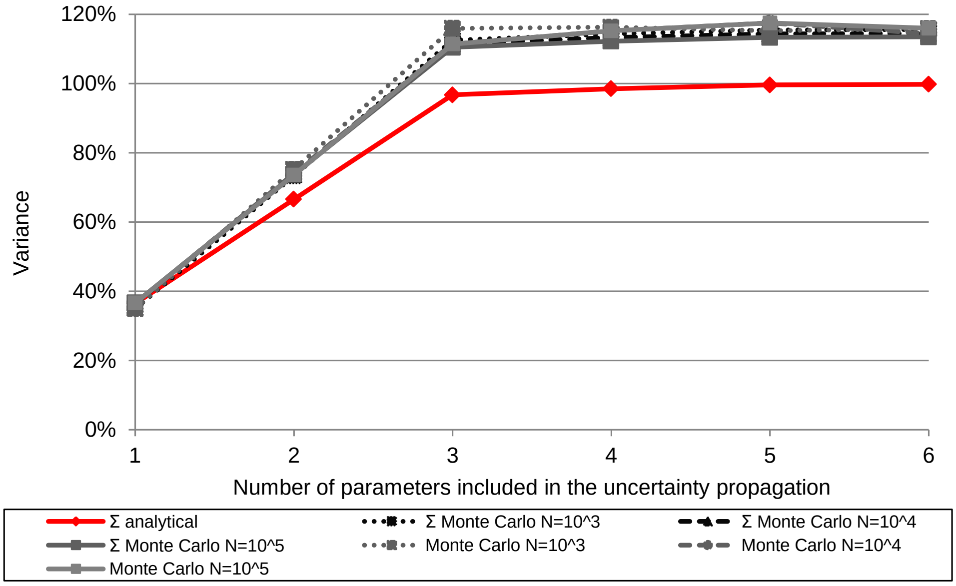
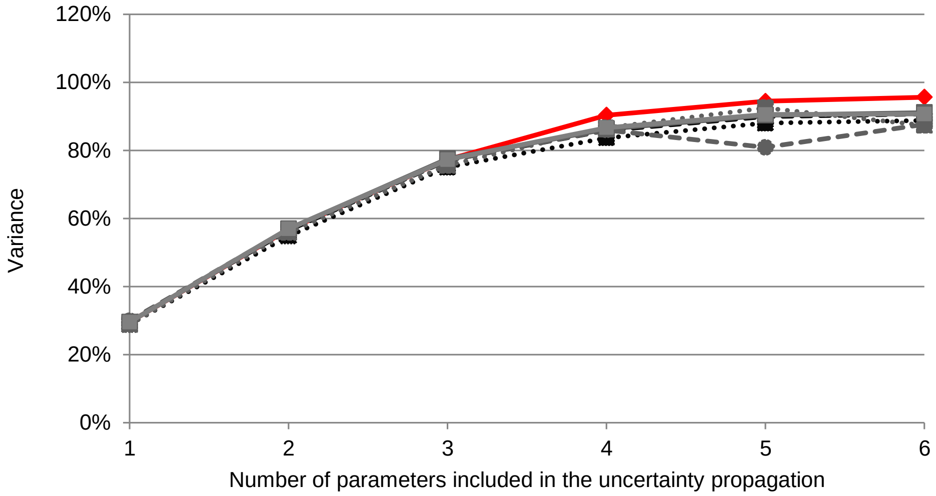
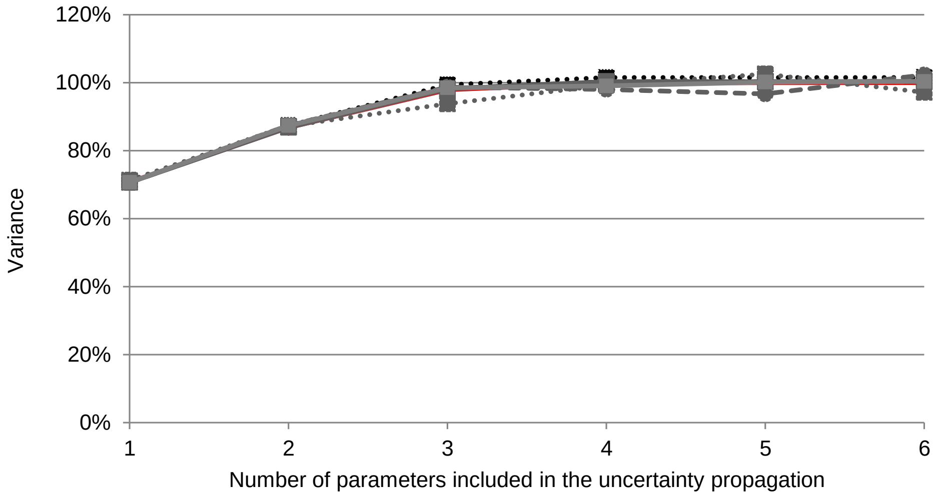


Figure S16. Additivity of variances for analytical (red) and sampling (grey) methods; HTnc impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

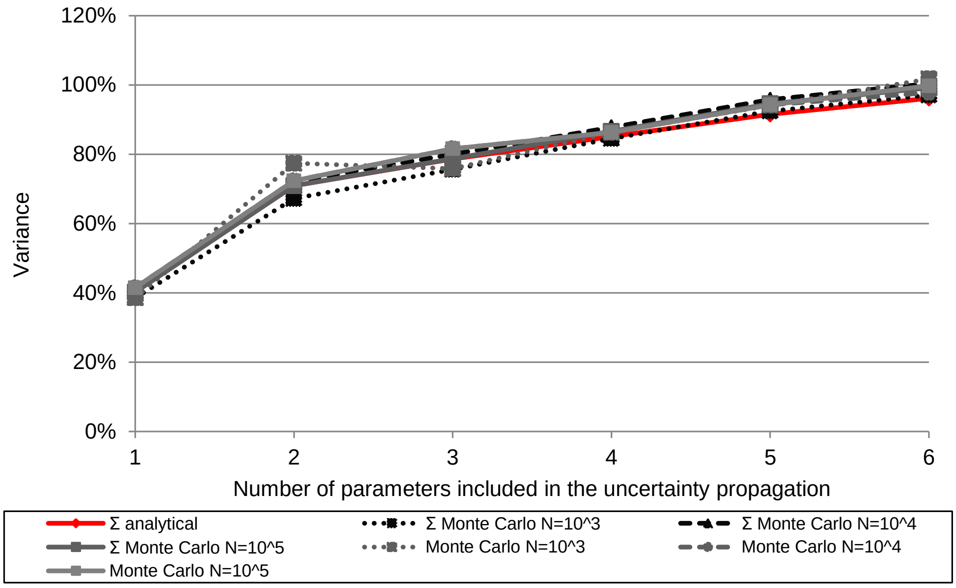
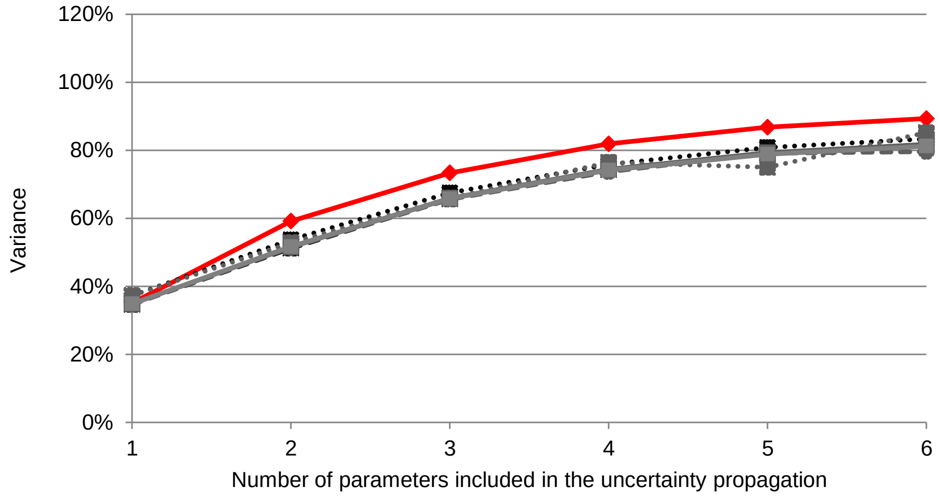
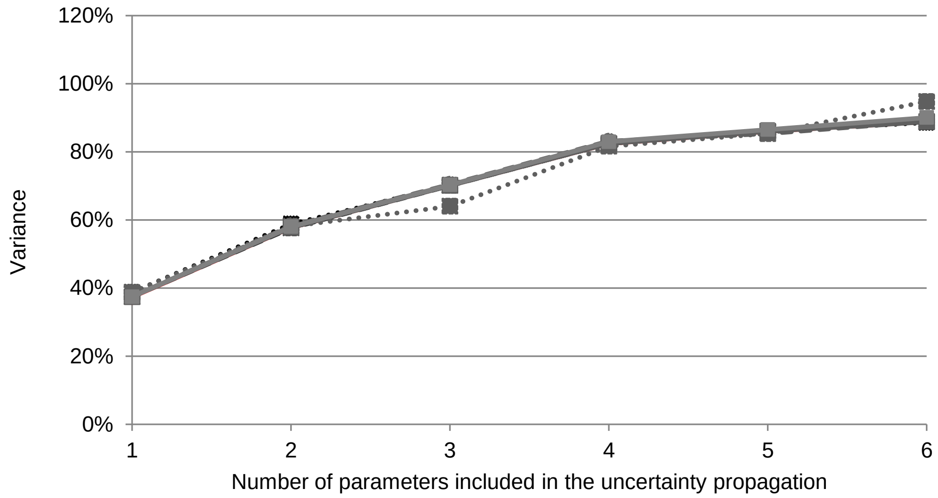


Figure S17. Additivity of variances for analytical (red) and sampling (grey) methods; PM impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

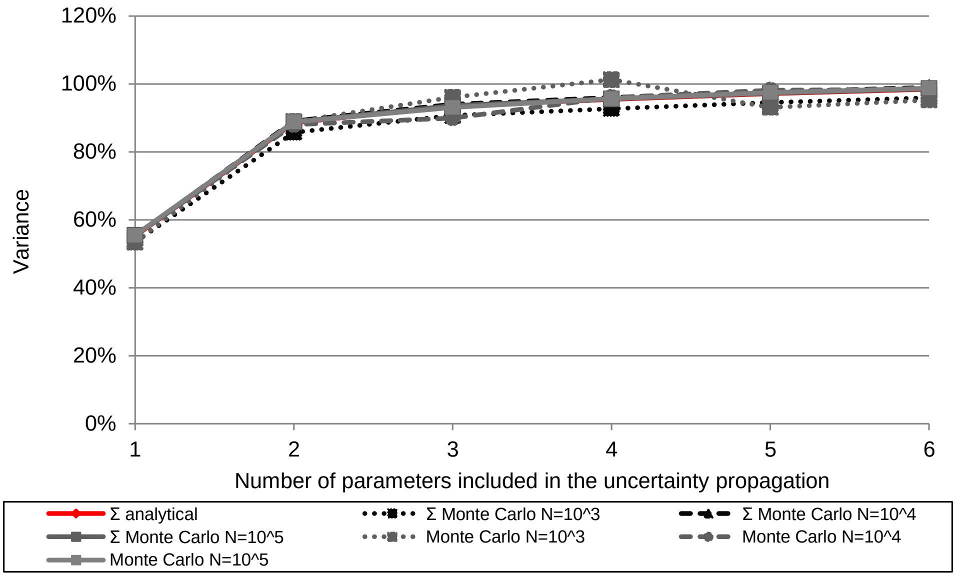
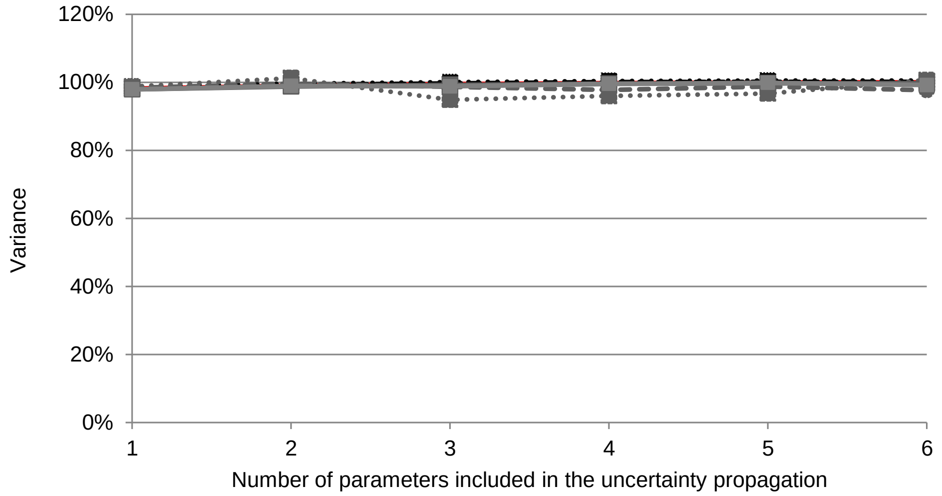
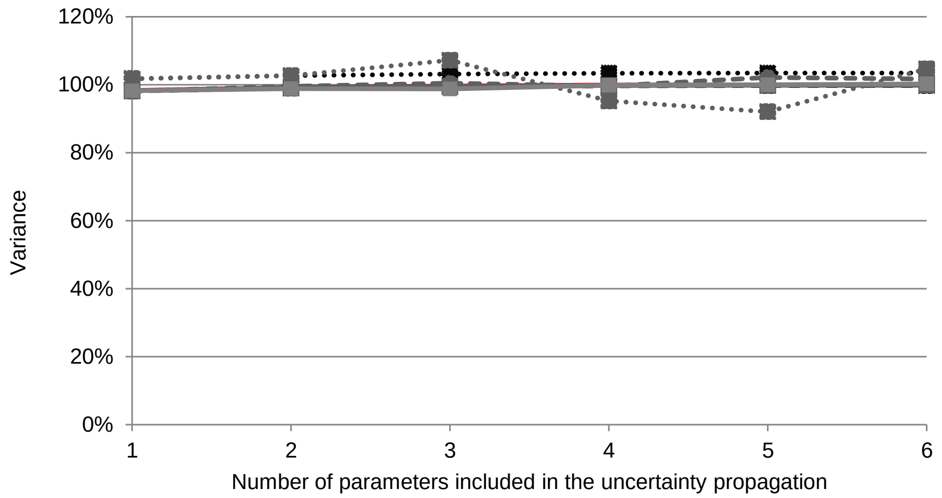


Figure S18. Additivity of variances for analytical (red) and sampling (grey) methods; IR impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

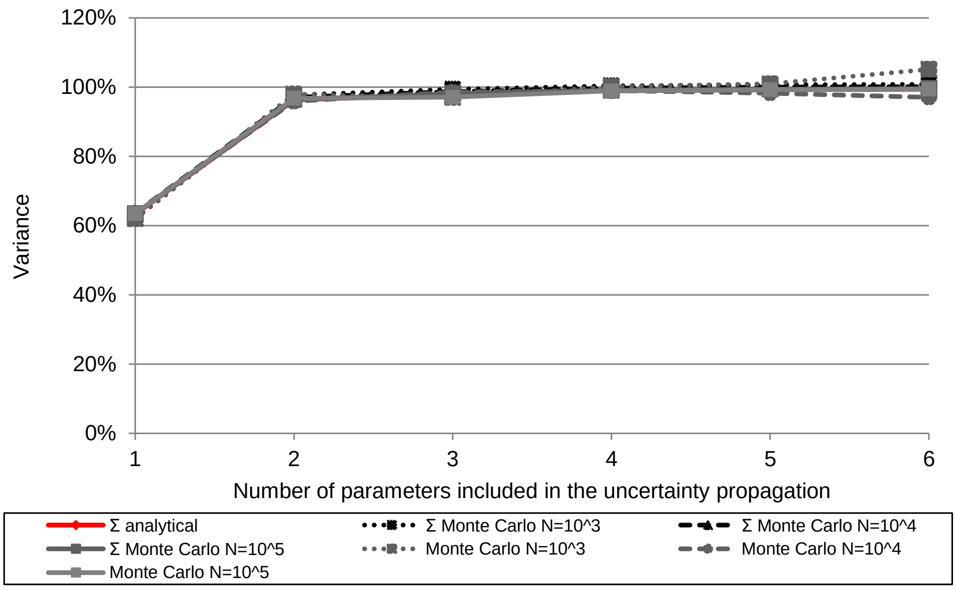
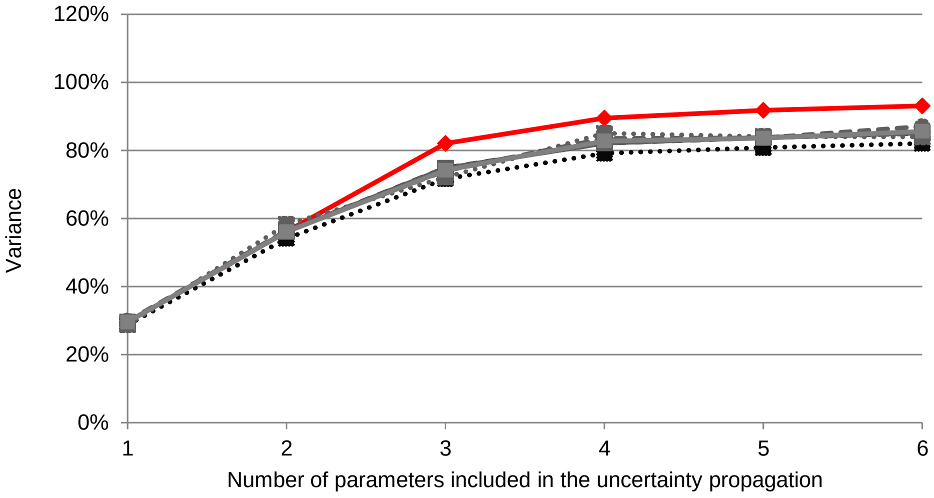
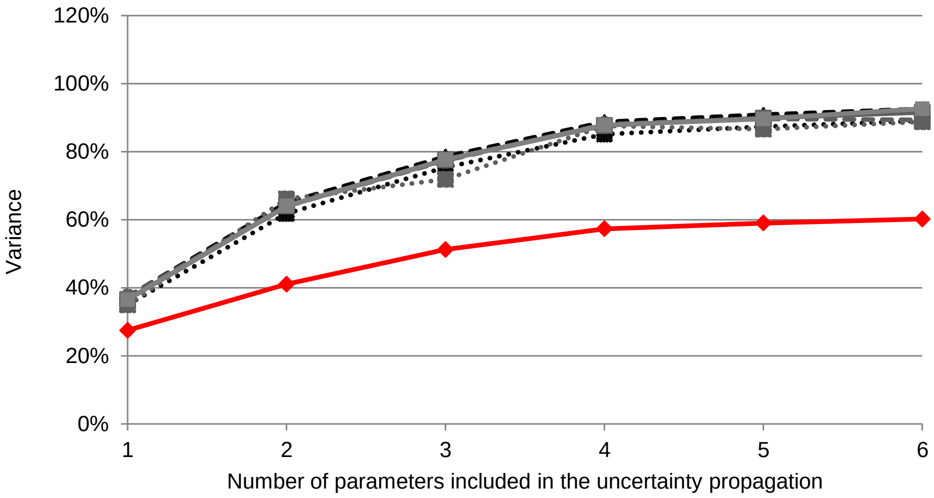


Figure S19. Additivity of variances for analytical (red) and sampling (grey) methods; POFP impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

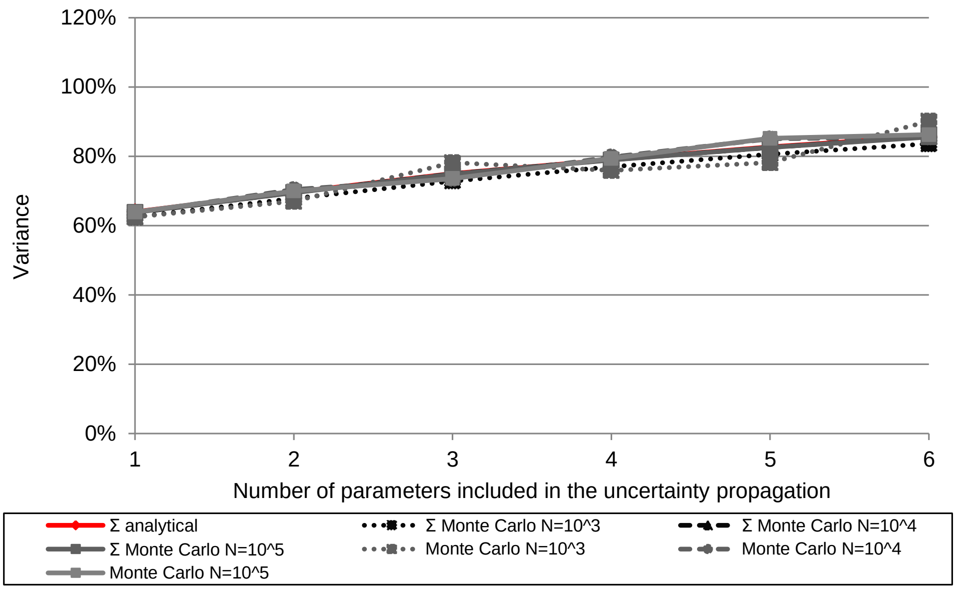
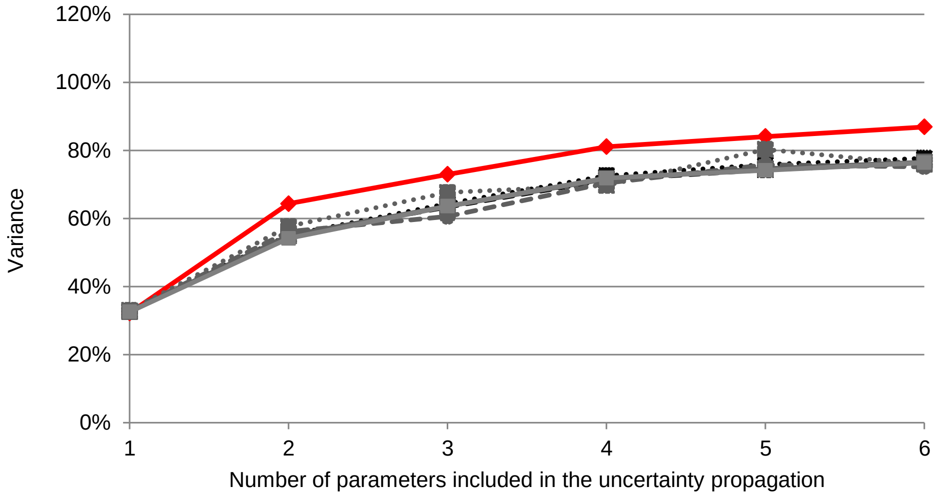
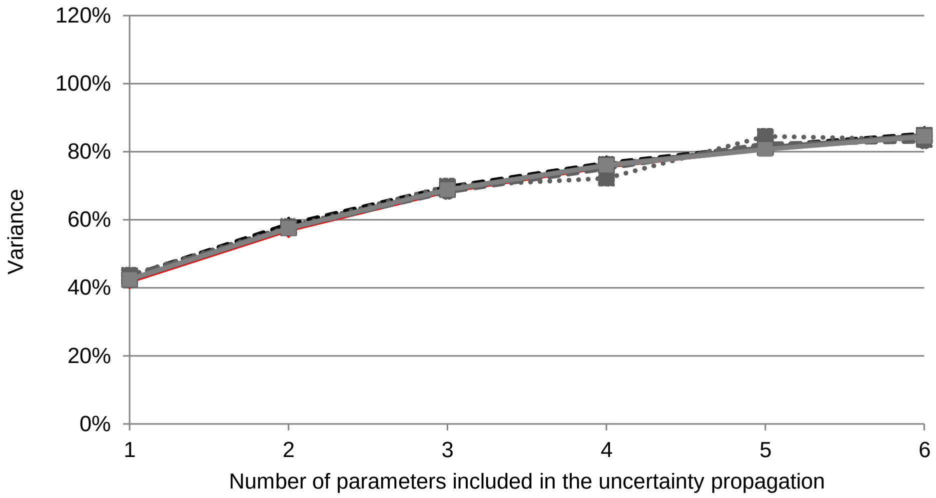


Figure S20. Additivity of variances for analytical (red) and sampling (grey) methods; TA impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

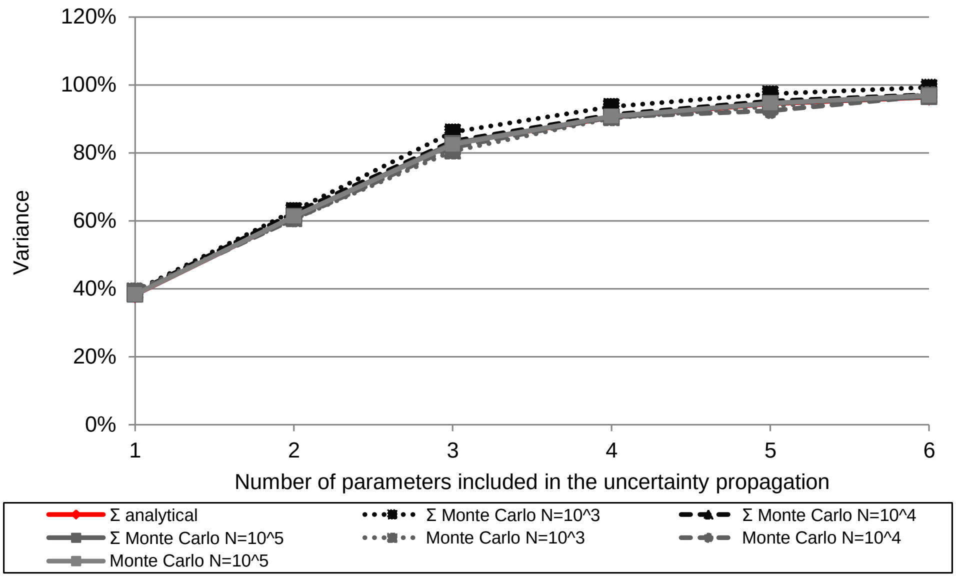
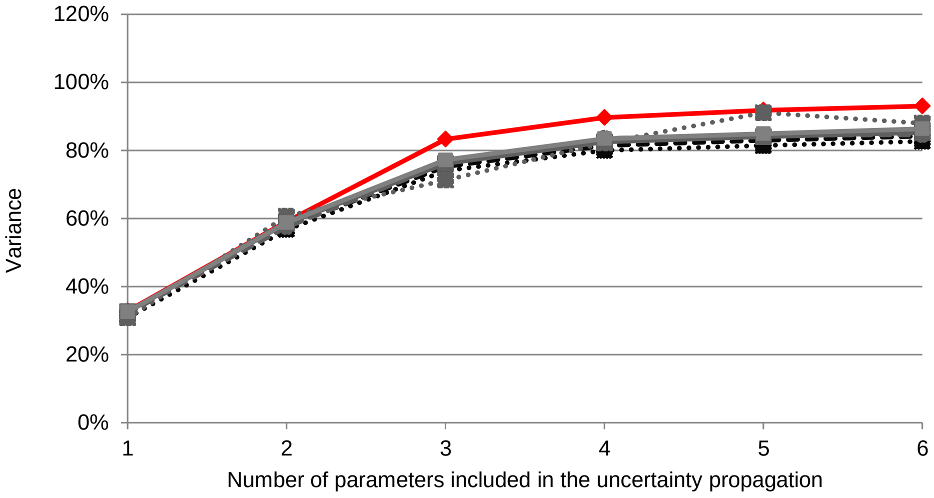
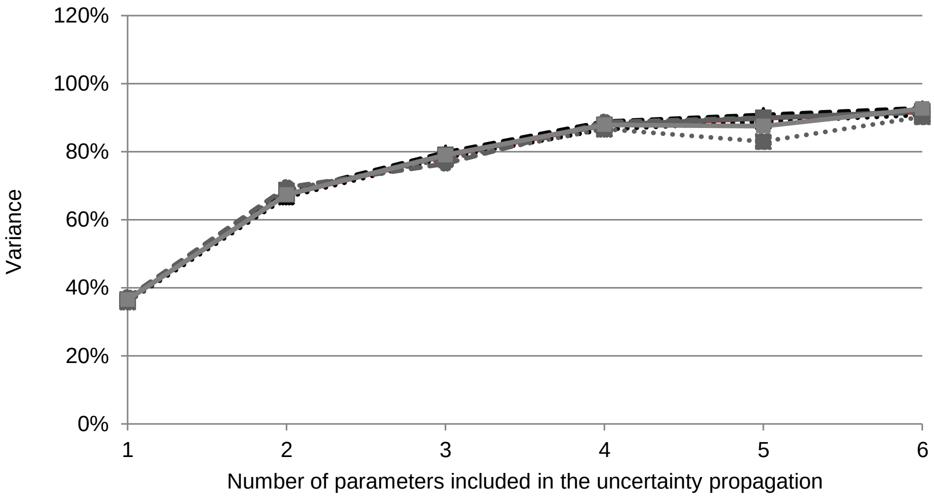


Figure S21. Additivity of variances for analytical (red) and sampling (grey) methods; TE impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

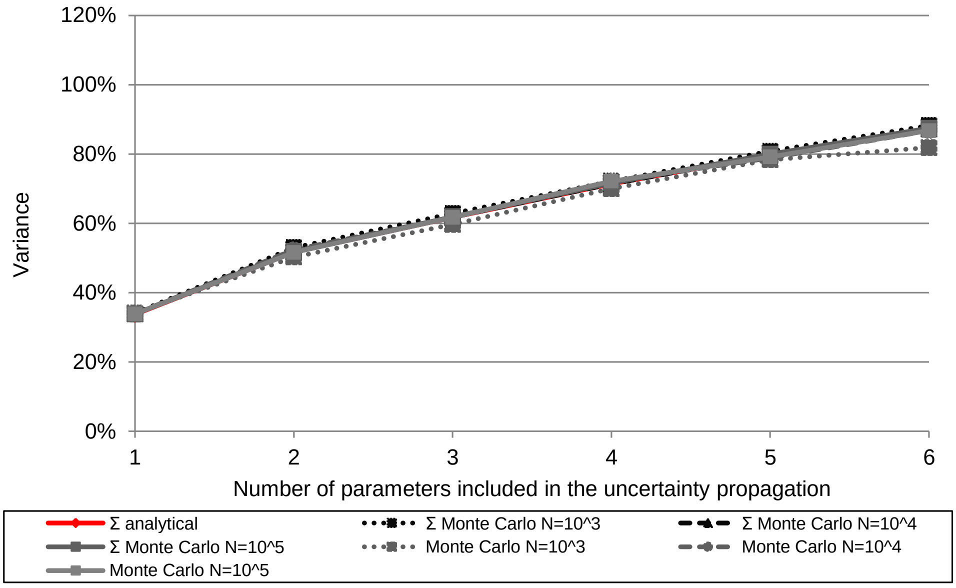
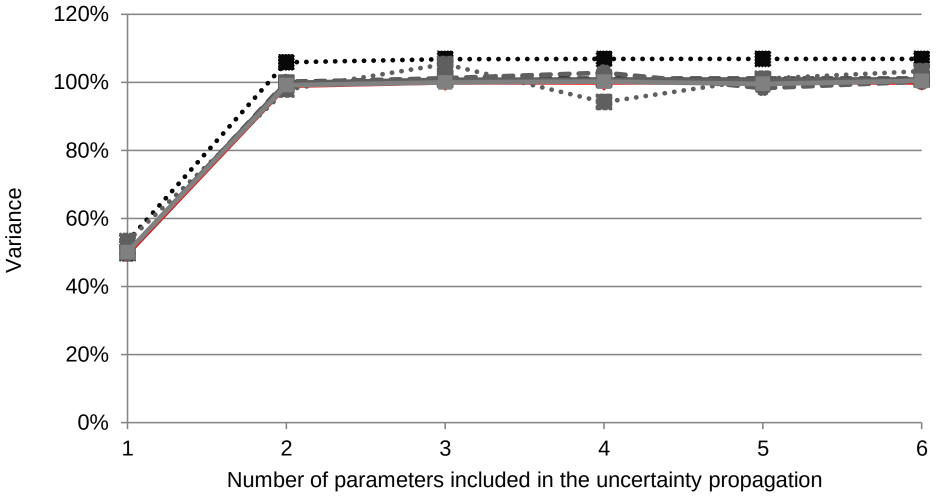
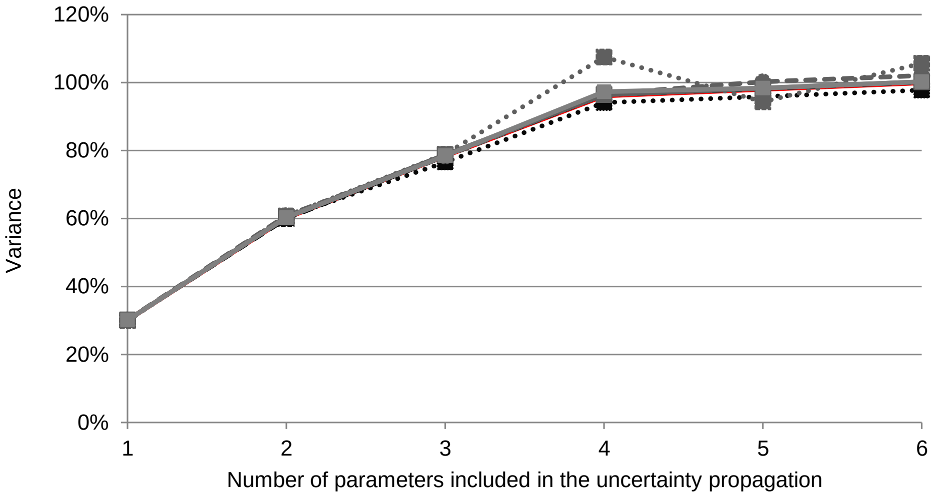


Figure S22. Additivity of variances for analytical (red) and sampling (grey) methods; FE impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

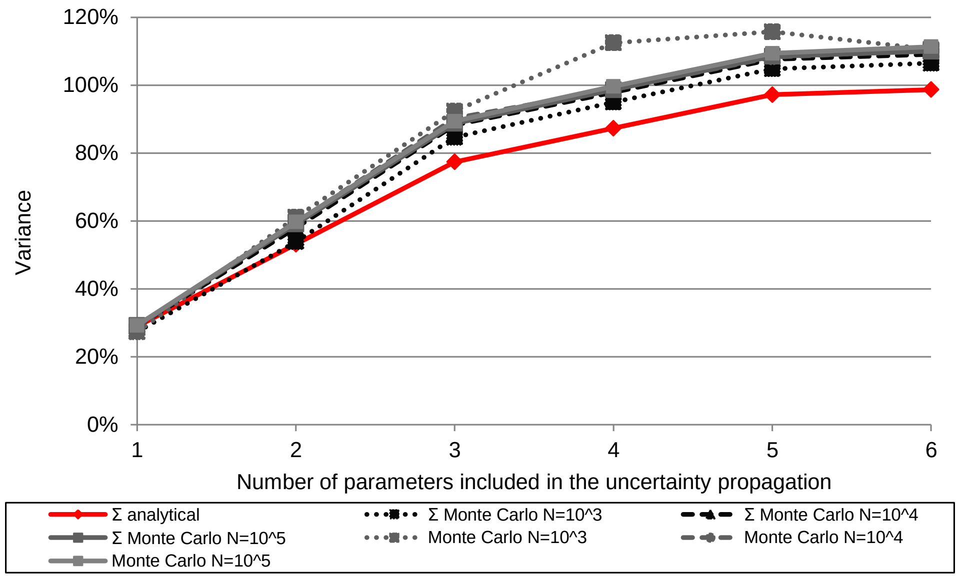
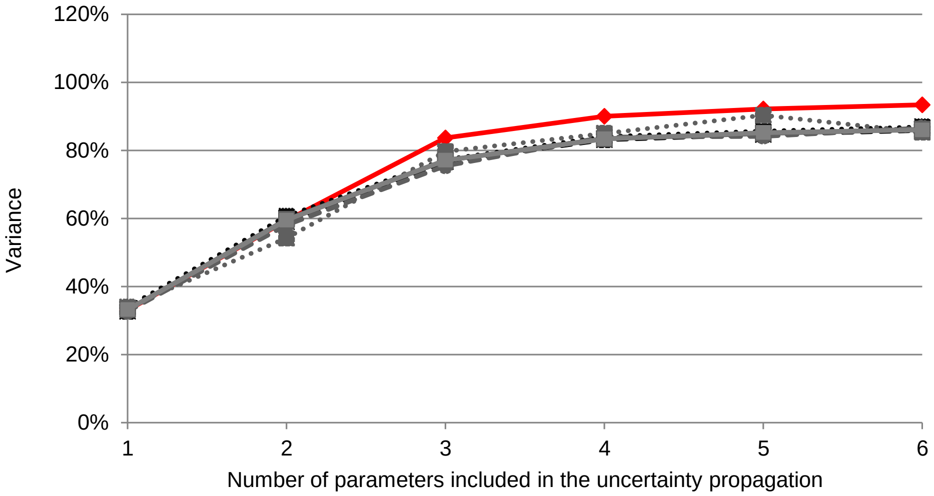
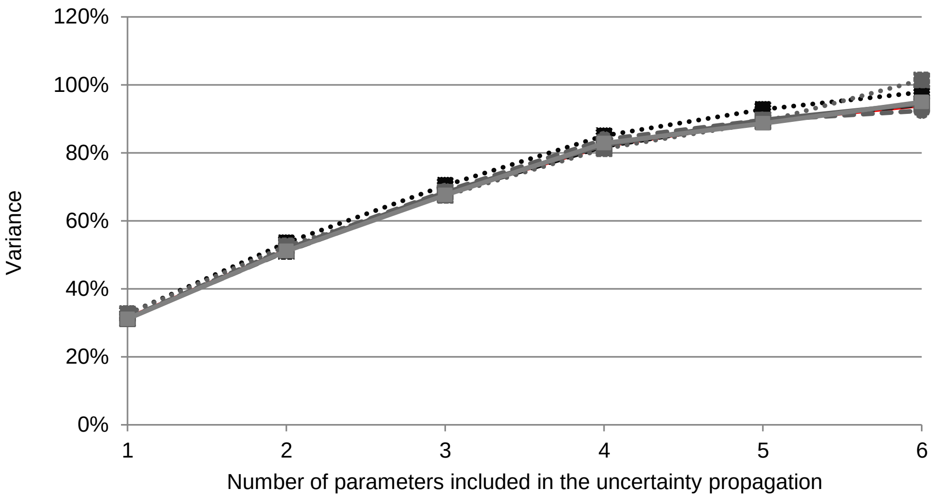


Figure S23. Additivity of variances for analytical (red) and sampling (grey) methods; ME impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

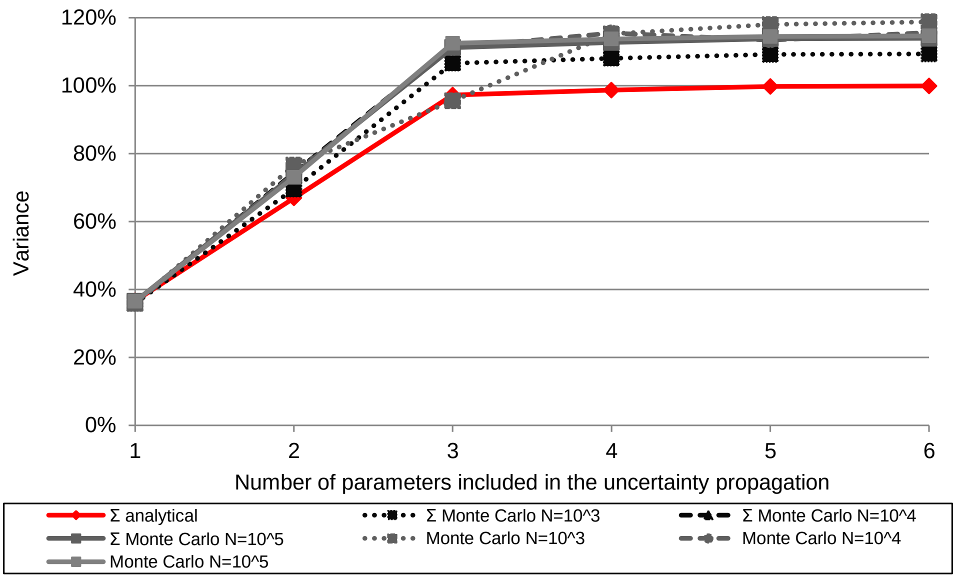
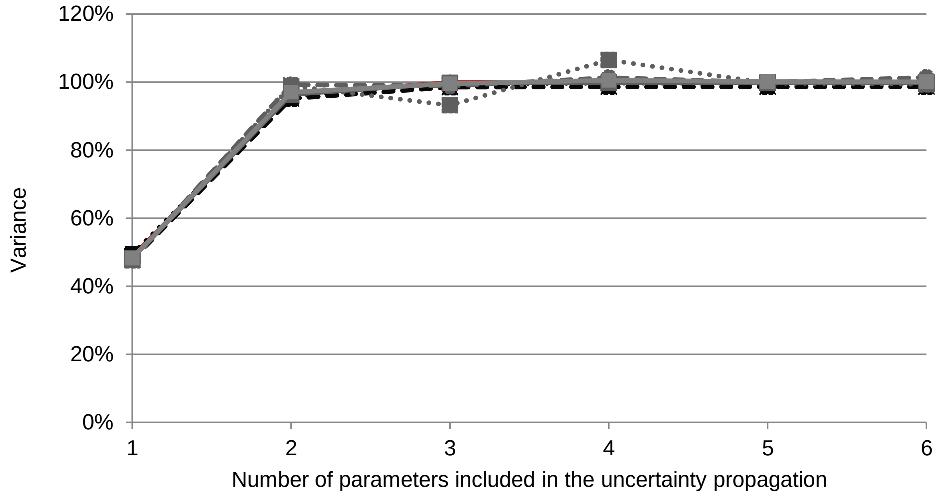
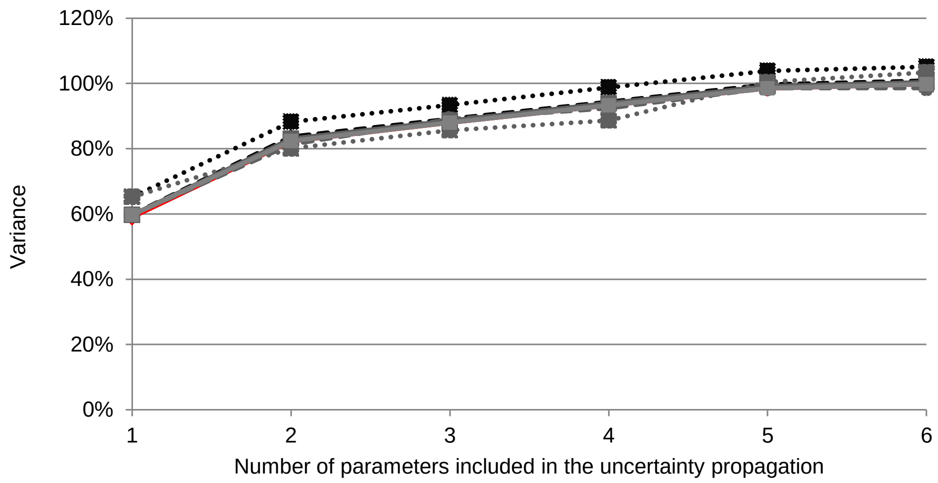


Figure S24. Additivity of variances for analytical (red) and sampling (grey) methods; ET impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

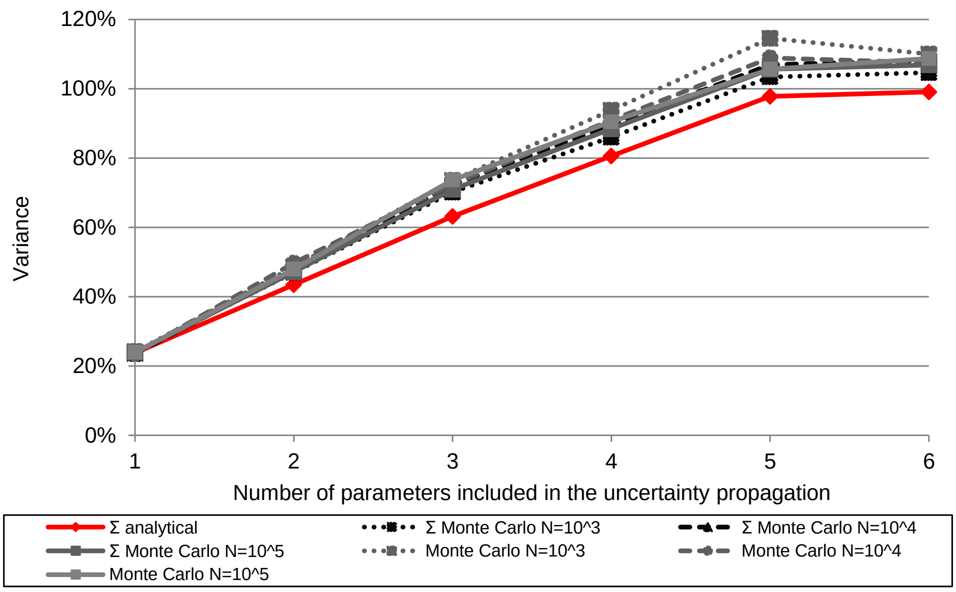
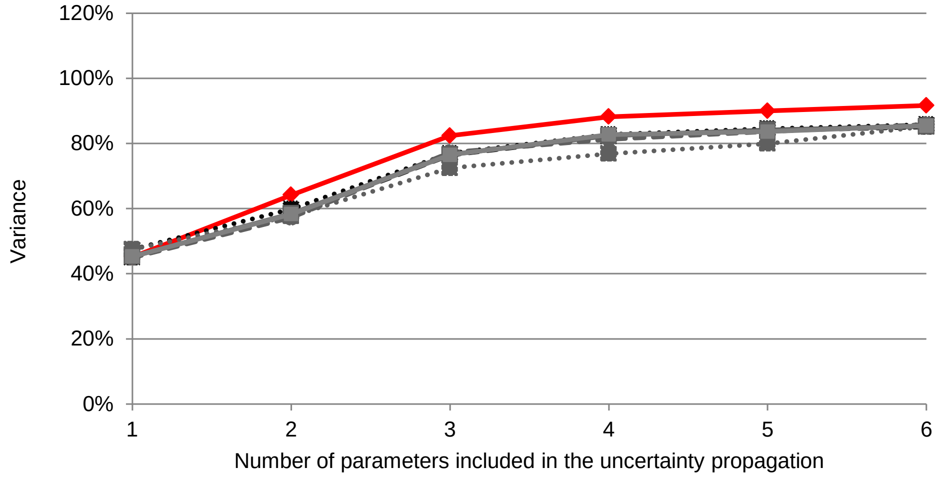
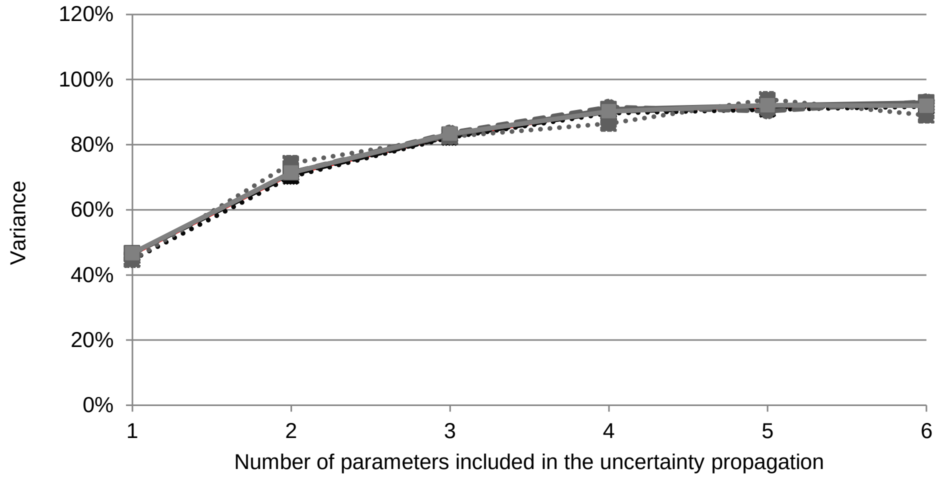


Figure S25. Additivity of variances for analytical (red) and sampling (grey) methods; RDfos impact category

(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

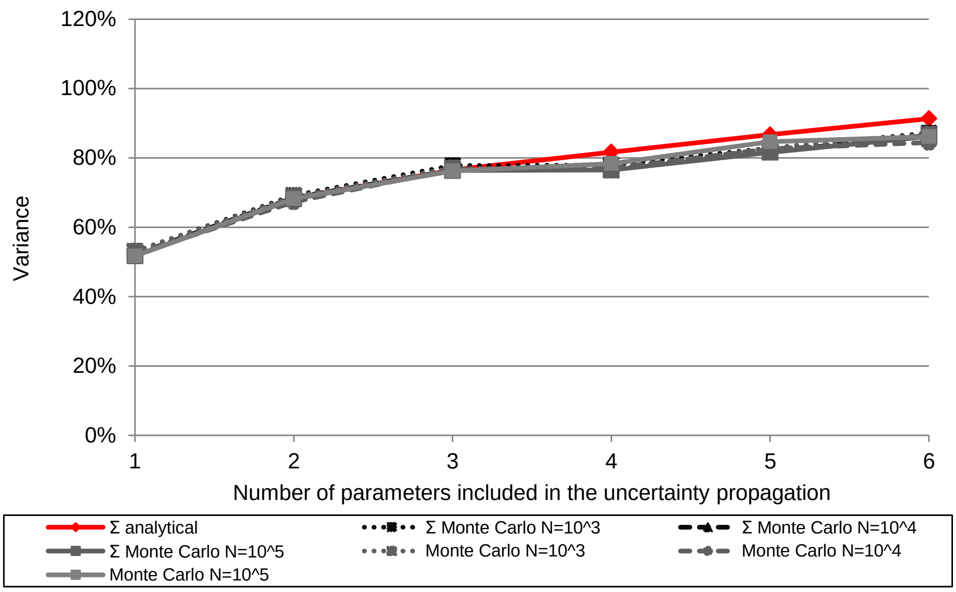
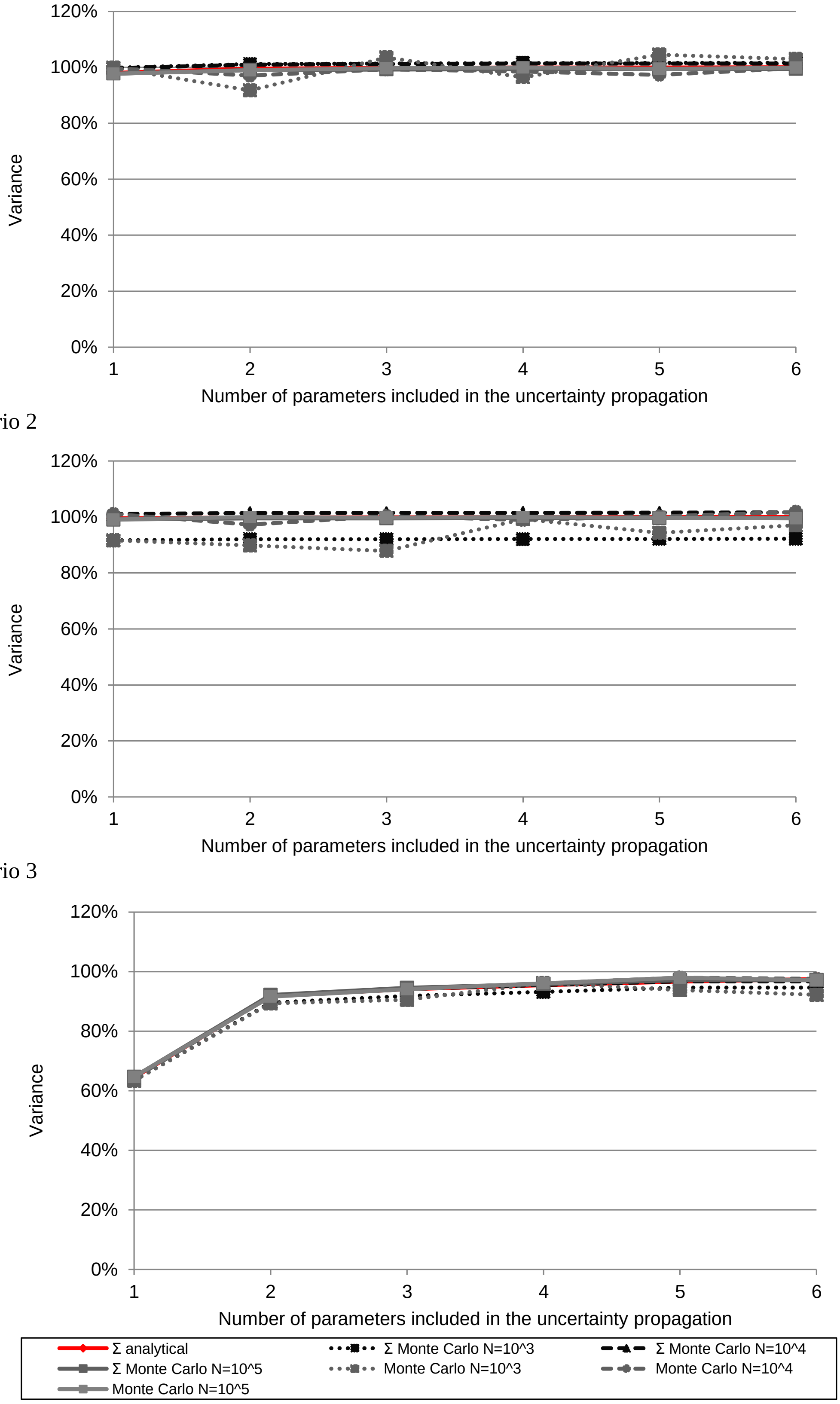


Figure S26. Additivity of variances for analytical (red) and sampling (grey) methods; RD impact category

(a) Scenario 1

(b) Scenario 2

(c) Scenario 3



SI.7 Applicability to other cases of uncertainty range and distribution type

This section provides an overview of previously tested cases where the uncertainty ranges and the probability distribution types differ from the assumptions presented in the main article. The following pages show how analytical uncertainty propagation and the GSA approach could still be solidly used for simplifying the uncertainty quantification, identifying a limited number of parameters characterizing most of the uncertainty and the results of the discernibility analysis across fourteen impact categories.

The results are subdivided into the following sub-sections:

A) All parameters have the same input uncertainties
   a. Centred distributions
   b. In-depth analysis of extremely skewed distributions

B) Parameters have different uncertainty ranges and distribution types ("real life" case example)

A) <u>All parameters have the same input uncertainty</u>

Methods

For Scenario 1, the eighty parameters identified with contribution analysis and tested in the article were subjected to increasing uncertainty ranges: 10 %, 20 % and 50 %. The uncertainty ranges were the same for all parameters within each tested case. Every uncertainty range increase was tested for the following distribution types:

- Normal distribution;
- Uniform distribution;
- Triangular distribution centred (mode = initial parameter value);
- Lognormal distribution;
- Triangular distribution skewed to the left (mode = minimum value in the range);
- Triangular distribution skewed to the right (mode = maximum value in the range).

The new input variance for each parameter was calculated for the different uncertainty distributions and uncertainty ranges with the formulas shown in the previous Section SI.3.

Then, the corresponding new analytical uncertainty values for each case could be easily calculated with Eq. (11) for individual parameters, since the SC values for each parameter for Scenario 1 obtained with Eq. (2) do not change. Consequently, the total output variance for Scenario 1 in each impact category could be calculated summing the individual parameters' contributions with Eq. (12). In parallel, the output uncertainty was also sampled for each case by means of a Monte Carlo analysis carried out with 1000 sampling points. This was carried out both for individual parameters and for the total set of parameters.

The percent difference from the total analytically calculated uncertainty and the total sampled uncertainty was calculated and discussed. An in-depth analysis was dedicated to the case of extremely skewed distributions. We also examined the hierarchies of the parameters based on their contribution to the output uncertainty (obtained both analytically and by means of Monte Carlo) for each case and for all the fourteen ILCD impact categories examined in the main article.

The full procedure was firstly carried out for the complete list of parameters presented in the article (eighty), and then for a smaller set (seventy) that excluded the moisture content related parameters.

Results and discussion

The SC values are related to the sensitivity of a parameter within a model irrespective of its input variance and are only based on the variation caused in the model result by a small equal variation in the parameters (10 % in this case). Therefore, since the model for Scenario 1 was not changed (but only the input variance associated to the model parameters), the SC values are unchanged.

Tables 1 – 4 show the analytically calculated and sampled total uncertainty for different uncertainty ranges for Scenario 1 for each of the fourteen ILCD impact categories. The percent variations between the two output uncertainties scores are shown in italics. Table 1 shows results for the normal distribution, Table 2 for the uniform, Table 3 for the triangular and Table 4 for the lognormal.

In the article we have shown that using 1000 sampling points for the Monte Carlo analysis was associated with the highest percent differences from the analytical method, and that these differences reduced for increasing numbers of Monte Carlo samples used in the analysis. In this case, using 1000 sampling points would therefore point out the highest variations between the analytical and the sampling method.

The percentage differences shown in Tables 1 – 4 are on average 4 % for the normal distribution, 7 % for the uniform, 3 % for the triangular and 5 % for the lognormal, complying with the observed average 6 % observed in the article. The largest variations were observed for the POFP and TA impact categories, as shown in Table 2 in the article. The variation between the analytical and the sampled uncertainty did not increase with higher uncertainty ranges.

Table S.22. Total output variance for Scenario 1 for each impact category and increasing input variance, normally distributed, assigned to the model parameters. The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are included.

	Normal distribution analytical			**Normal distribution MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	2.25E-05	9.00E-05	5.63E-04	2.12E-05	8.73E-05	5.57E-04	*6%*	*3%*	*1%*
ODP	1.01E-11	4.05E-11	2.53E-10	1.03E-11	4.25E-11	2.69E-10	*-2%*	*-5%*	*-6%*
HTC	2.41E-09	9.65E-09	6.03E-08	2.14E-09	9.58E-09	6.12E-08	*13%*	*1%*	*-1%*
HTNC	1.29E-07	5.14E-07	3.21E-06	1.13E-07	4.94E-07	3.18E-06	*14%*	*4%*	*1%*
PM	1.13E-06	4.53E-06	2.83E-05	9.52E-07	4.15E-06	2.58E-05	*19%*	*9%*	*10%*
IR	6.70E-08	2.68E-07	1.68E-06	6.78E-08	2.80E-07	1.77E-06	*-1%*	*-4%*	*-5%*
POFP	1.32E-06	5.29E-06	3.31E-05	1.21E-06	4.77E-06	3.13E-05	*9%*	*11%*	*6%*
TA	3.45E-06	1.38E-05	8.63E-05	3.03E-06	1.18E-05	7.84E-05	*14%*	*17%*	*10%*
TE	5.26E-06	2.10E-05	1.31E-04	4.86E-06	1.92E-05	1.25E-04	*8%*	*9%*	*5%*
FE	1.91E-09	7.63E-09	4.77E-08	1.87E-09	7.88E-09	4.51E-08	*2%*	*-3%*	*6%*
ME	6.55E-06	2.62E-05	1.64E-04	6.05E-06	2.38E-05	1.56E-04	*8%*	*10%*	*5%*
ET	2.23E-05	8.91E-05	5.57E-04	2.18E-05	9.10E-05	5.95E-04	*2%*	*-2%*	*-6%*
RDFOS	4.18E-05	1.67E-04	1.05E-03	3.62E-05	1.55E-04	1.00E-03	*15%*	*8%*	*4%*
RD	1.34E-12	5.35E-12	3.35E-11	1.37E-12	5.58E-12	3.49E-11	*-2%*	*-4%*	*-4%*

Table S23. Total output variance for Scenario 1 for each impact category and increasing input variance, uniformly distributed, assigned to the model parameters. The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are included.

	Uniform distribution analytical			**Uniform distribution MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	3.00E-05	1.20E-04	7.50E-04	3.09E-05	1.10E-04	6.97E-04	*-3%*	*9%*	*8%*
ODP	1.35E-11	5.40E-11	3.38E-10	1.34E-11	5.49E-11	3.34E-10	*1%*	*-2%*	*1%*
HTC	3.22E-09	1.29E-08	8.04E-08	3.23E-09	1.18E-08	7.49E-08	*0%*	*9%*	*7%*
HTNC	1.71E-07	6.86E-07	4.28E-06	1.65E-07	6.21E-07	3.98E-06	*4%*	*10%*	*8%*
PM	1.51E-06	6.04E-06	3.77E-05	1.44E-06	5.08E-06	3.23E-05	*5%*	*19%*	*17%*
IR	8.94E-08	3.58E-07	2.23E-06	8.83E-08	3.62E-07	2.20E-06	*1%*	*-1%*	*2%*
POFP	1.76E-06	7.05E-06	4.41E-05	1.61E-06	5.96E-06	4.02E-05	*9%*	*18%*	*10%*
TA	4.61E-06	1.84E-05	1.15E-04	4.23E-06	1.49E-05	9.89E-05	*9%*	*24%*	*16%*
TE	7.01E-06	2.80E-05	1.75E-04	6.41E-06	2.40E-05	1.62E-04	*9%*	*17%*	*8%*
FE	2.54E-09	1.02E-08	6.36E-08	2.53E-09	1.01E-08	6.37E-08	*0%*	*0%*	*0%*
ME	8.73E-06	3.49E-05	2.18E-04	7.99E-06	2.99E-05	2.02E-04	*9%*	*17%*	*8%*
ET	2.97E-05	1.19E-04	7.43E-04	2.96E-05	1.17E-04	7.76E-04	*0%*	*1%*	*-4%*
RDFOS	5.58E-05	2.23E-04	1.39E-03	5.32E-05	2.00E-04	1.23E-03	*5%*	*11%*	*13%*
RD	1.78E-12	7.14E-12	4.46E-11	1.77E-12	6.89E-12	4.48E-11	*1%*	*4%*	*0%*

Table S24. Total output variance for Scenario 1 for each impact category and increasing input variance, triangularly distributed (centred), assigned to the model parameters. The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are included.

	Triangular distribution analytical			**Triangular distribution MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	1.50E-05	6.00E-05	3.75E-04	1.56E-05	6.23E-05	3.85E-04	*-4%*	*-4%*	*-3%*
ODP	6.75E-12	2.70E-11	1.69E-10	7.04E-12	2.75E-11	1.69E-10	*-4%*	*-2%*	*0%*
HTC	1.61E-09	6.43E-09	4.02E-08	1.54E-09	5.99E-09	3.83E-08	*5%*	*7%*	*5%*
HTNC	8.57E-08	3.43E-07	2.14E-06	8.14E-08	3.17E-07	2.00E-06	*5%*	*8%*	*7%*
PM	7.55E-07	3.02E-06	1.89E-05	6.95E-07	2.77E-06	1.74E-05	*9%*	*9%*	*8%*
IR	4.47E-08	1.79E-07	1.12E-06	4.64E-08	1.81E-07	1.12E-06	*-4%*	*-1%*	*0%*
POFP	8.81E-07	3.53E-06	2.20E-05	8.31E-07	3.37E-06	2.20E-05	*6%*	*4%*	*0%*
TA	2.30E-06	9.21E-06	5.76E-05	2.16E-06	8.35E-06	5.54E-05	*6%*	*10%*	*4%*
TE	3.50E-06	1.40E-05	8.76E-05	3.32E-06	1.35E-05	8.79E-05	*5%*	*4%*	*0%*
FE	1.27E-09	5.08E-09	3.18E-08	1.25E-09	4.76E-09	3.03E-08	*2%*	*7%*	*5%*
ME	4.36E-06	1.75E-05	1.09E-04	4.14E-06	1.69E-05	1.09E-04	*5%*	*4%*	*0%*
ET	1.49E-05	5.94E-05	3.71E-04	1.55E-05	5.72E-05	3.58E-04	*-4%*	*4%*	*4%*
RDFOS	2.79E-05	1.12E-04	6.97E-04	2.66E-05	1.04E-04	6.63E-04	*5%*	*7%*	*5%*
RD	8.92E-13	3.57E-12	2.23E-11	9.47E-13	3.55E-12	2.28E-11	*-6%*	*1%*	*-2%*

Table S25. Total output variance for Scenario 1 for each impact category and increasing input variance, lognormally distributed, assigned to the model parameters. The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are included.

	Lognormal distribution analytical			**Lognormal distribution MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	2.25E-05	9.00E-05	5.63E-04	2.24E-05	9.18E-05	5.62E-04	*0%*	*-2%*	*0%*
ODP	1.01E-11	4.05E-11	2.53E-10	1.08E-11	4.00E-11	2.38E-10	*-6%*	*1%*	*6%*
HTC	2.41E-09	9.65E-09	6.03E-08	2.19E-09	9.69E-09	5.89E-08	*10%*	*0%*	*2%*
HTNC	1.29E-07	5.14E-07	3.21E-06	1.15E-07	5.04E-07	3.06E-06	*12%*	*2%*	*5%*
PM	1.13E-06	4.53E-06	2.83E-05	9.81E-07	4.15E-06	2.58E-05	*15%*	*9%*	*10%*
IR	6.70E-08	2.68E-07	1.68E-06	7.13E-08	2.64E-07	1.57E-06	*-6%*	*2%*	*7%*
POFP	1.32E-06	5.29E-06	3.31E-05	1.22E-06	4.68E-06	3.09E-05	*9%*	*13%*	*7%*
TA	3.45E-06	1.38E-05	8.63E-05	3.11E-06	1.23E-05	7.69E-05	*11%*	*12%*	*12%*
TE	5.26E-06	2.10E-05	1.31E-04	4.88E-06	1.87E-05	1.24E-04	*8%*	*13%*	*6%*
FE	1.91E-09	7.63E-09	4.77E-08	1.93E-09	7.70E-09	4.66E-08	*-1%*	*-1%*	*2%*
ME	6.55E-06	2.62E-05	1.64E-04	6.07E-06	2.32E-05	1.54E-04	*8%*	*13%*	*6%*
ET	2.23E-05	8.91E-05	5.57E-04	2.10E-05	9.28E-05	5.78E-04	*6%*	*-4%*	*-4%*
RDFOS	4.18E-05	1.67E-04	1.05E-03	3.79E-05	1.60E-04	9.90E-04	*10%*	*5%*	*6%*
RD	1.34E-12	5.35E-12	3.35E-11	1.26E-12	5.24E-12	3.64E-11	*6%*	*2%*	*-8%*

Tables S22 – S25 show that for increasing uncertainty ranges, the total output variance for each impact category increases accordingly. The same happens to the output uncertainty of each parameter. Tables S26 – S29 report the hierarchies of the contributions of the model parameters to the total uncertainty. The values shown in the tables were calculated analytically.

When the uncertainty range given to all parameters is the same, the ranking between parameters will be unchanged and correspondent to the one obtained for the sensitivity analysis (with the absolute value of the SRs, Eq. (1)), irrespective of the uncertainty range or the distribution type.

Since the analytical method showed the same contained variation from the Monte Carlo results for different uncertainty ranges and distribution types, we observe that in all these cases the uncertainty can be well represented by the same parameters identified in the article (normal distribution, 10 % variation for all parameters). Therefore, considering the six highest ranking parameters per impact category, corresponding to ten parameters out of the initial eighty across all fourteen impact categories, it is possible to represent up to 90 % of the output uncertainty. Moreover, even when the total output uncertainty increases, the parameters are associated to the same share of contribution (Tables S26 – S29).

Finally, in the article we evidenced how interdependent parameters (especially water content related parameters) were mostly responsible for the deviation between the analytical and the sampled uncertainty values. We carried out the same analysis discussed above for Scenario 1 after decoupling such parameters. Results are reported in Tables S30 – S33. The difference between the analytical method and the Monte Carlo sampling reduces further, with an average 1 % for normal, uniform and triangular distributions, and 2 % for the lognormal case.

Table S26. Analytically calculated output variances for the impact category GWP, for normally distributed parameters with increasing uncertainty. The values are rank-ordered according to their contribution to the total analytical output variance. The percentage of the represented analytical variance for the corresponding number of parameters is reported.

Normal distribution, GWP									
	Uncertainty: 10%			Uncertainty: 20%			Uncertainty: 50%		
	Parameter	Output variance [PE^2]	*Represented of total [%]*	Parameter	Output variance [PE^2]	*Represented of total [%]*	Parameter	Output variance [PE^2]	*Represented of total [%]*
1	Electricity recovery	7.1E-06	*32%*	Electricity recovery	2.8E-05	*32%*	Electricity recovery	0.00018	*32%*
2	Water content, vegetable waste	5.4E-06	*56%*	Water content, vegetable waste	2.2E-05	*56%*	Water content, vegetable waste	0.00014	*56%*
3	Paper recycling	3.4E-06	*71%*	Paper recycling	1.3E-05	*71%*	Paper recycling	8.4E-05	*71%*
4	Heat recovery	2.3E-06	*81%*	Heat recovery	9E-06	*81%*	Heat recovery	5.6E-05	*81%*
5	Segregated paper	2.1E-06	*90%*	Segregated paper	8.4E-06	*90%*	Segregated paper	5.3E-05	*90%*
6	Water content, animal food waste	4.6E-07	*92%*	Water content, animal food waste	1.8E-06	*92%*	Water content, animal food waste	1.1E-05	*92%*
7	Heating value, vegetable food waste	3.7E-07	*94%*	Heating value, vegetable food waste	1.5E-06	*94%*	Heating value, vegetable food waste	9.2E-06	*94%*
8	Heating value, plastic waste	3.4E-07	*95%*	Heating value, plastic waste	1.3E-06	*95%*	Heating value, plastic waste	8.4E-06	*95%*
9	Fossil carbon content, plastic waste	2.6E-07	*96%*	Fossil carbon content, plastic waste	1E-06	*96%*	Fossil carbon content, plastic waste	6.4E-06	*96%*
10	Heating value, animal food waste	2.2E-07	*97%*	Heating value, animal food waste	8.6E-07	*97%*	Heating value, animal food waste	5.4E-06	*97%*

Table S27. Analytically calculated output variances for the impact category GWP, for uniformly distributed parameters with increasing uncertainty. The values are rank-ordered according to their contribution to the total analytical output variance. The percentage of the represented analytical variance for the corresponding number of parameters is reported.

Uniform distribution, GWP									
	Uncertainty: 10%			Uncertainty: 20%			Uncertainty: 50%		
	Parameter	Output variance [PE^2]	*Represented of total [%]*	Parameter	Output variance [PE^2]	*Represented of total [%]*	Parameter	Output variance [PE^2]	*Represented of total [%]*
1	Electricity recovery	9.46E-06	*32%*	Electricity recovery	3.8E-05	*32%*	Electricity recovery	2.4E-44	*32%*
2	Water content, vegetable waste	7.20E-06	*56%*	Water content, vegetable waste	2.9E-05	*56%*	Water content, vegetable waste	1.8E-04	*56%*
3	Paper recycling	4.49E-06	*71%*	Paper recycling	1.8E-05	*71%*	Paper recycling	1.1E-04	*71%*
4	Heat recovery	3E-06	*81%*	Heat recovery	1.2E-05	*81%*	Heat recovery	7.5E-05	*81%*
5	Segregated paper	2.81E-06	*90%*	Segregated paper	1.1E-05	*90%*	Segregated paper	7E-05	*90%*
6	Water content, animal food waste	6.13E-07	*92%*	Water content, animal food waste	2.5E-06	*92%*	Water content, animal food waste	1.5E-05	*92%*
7	Heating value, vegetable food waste	4.88E-07	*94%*	Heating value, vegetable food waste	2E-06	*94%*	Heating value, vegetable food waste	1.2E-05	*94%*
8	Heating value, plastic waste	4.48E-07	*95%*	Heating value, plastic waste	1.8E-06	*95%*	Heating value, plastic waste	1.1E-05	*95%*
9	Fossil carbon content, plastic waste	3.40E-07	*96%*	Fossil carbon content, plastic waste	1.4E-06	*96%*	Fossil carbon content, plastic waste	8.5E-06	*96%*
10	Heating value, animal food waste	2.88E-07	*97%*	Heating value, animal food waste	1.2E-06	*97%*	Heating value, animal food waste	7.2E-06	*97%*

Table S28. Analytically calculated output variances for the impact category GWP, for triangularly distributed parameters with increasing uncertainty. The values are rank-ordered according to their contribution to the total analytical output variance. The percentage of the represented analytical variance for the corresponding number of parameters is reported.

Triangular distribution, GWP									
	Uncertainty: 10%			Uncertainty: 20%			Uncertainty: 50%		
	Parameter	Output variance	*Represented of total*	Parameter	Output variance	*Represented of total*	Parameter	Output variance	*Represented of total*
		[PE^2]	*[%]*		[PE^2]	*[%]*		[PE^2]	*[%]*
1	Electricity recovery	4.7E-06	*32%*	Electricity recovery	1.9E-05	*32%*	Electricity recovery	1.2E-04	*32%*
2	Water content, vegetable waste	3.6E-06	*56%*	Water content, vegetable waste	1.4E-05	*56%*	Water content, vegetable waste	9.0E-05	*56%*
3	Paper recycling	2.2E-06	*71%*	Paper recycling	9.0E-06	*71%*	Paper recycling	5.6E-05	*71%*
4	Heat recovery	1.5E-06	*81%*	Heat recovery	6.0E-06	*81%*	Heat recovery	3.8E-05	*81%*
5	Segregated paper	1.4E-06	*90%*	Segregated paper	5.6E-06	*90%*	Segregated paper	3.5E-05	*90%*
6	Water content, animal food waste	3.1E-07	*92%*	Water content, animal food waste	1.2E-06	*92%*	Water content, animal food waste	7.7E-06	*92%*
7	Heating value, vegetable food waste	2.4E-07	*94%*	Heating value, vegetable food waste	9.8E-07	*94%*	Heating value, vegetable food waste	6.1E-06	*94%*
8	Heating value, plastic waste	2.2E-07	*95%*	Heating value, plastic waste	9.0E-07	*95%*	Heating value, plastic waste	5.6E-06	*95%*
9	Fossil carbon content, plastic waste	1.7E-07	*96%*	Fossil carbon content, plastic waste	6.8E-07	*96%*	Fossil carbon content, plastic waste	4.3E-06	*96%*
10	Heating value, animal food waste	1.4E-07	*97%*	Heating value, animal food waste	5.8E-07	*97%*	Heating value, animal food waste	3.6E-06	*97%*

Table S29. Analytically calculated output variances for the impact category GWP, for lognormally distributed parameters with increasing uncertainty. The values are rank-ordered according to their contribution to the total analytical output variance. The percentage of the represented analytical variance for the corresponding number of parameters is reported.

Lognormal distribution, GWP									
	Uncertainty: 10%			Uncertainty: 20%			Uncertainty: 50%		
	Parameter	Output variance [PE^2]	*Represented of total [%]*	Parameter	Output variance [PE^2]	*Represented of total [%]*	Parameter	Output variance [PE^2]	*Represented of total [%]*
1	Electricity recovery	7.1E-06	*32%*	Electricity recovery	2.8E-05	*32%*	Electricity recovery	0.00018	*32%*
2	Water content, vegetable waste	5.4E-06	*56%*	Water content, vegetable waste	2.2E-05	*56%*	Water content, vegetable waste	0.00014	*56%*
3	Paper recycling	3.4E-06	*71%*	Paper recycling	1.3E-05	*71%*	Paper recycling	8.4E-05	*71%*
4	Heat recovery	2.3E-06	*81%*	Heat recovery	9E-06	*81%*	Heat recovery	5.6E-05	*81%*
5	Segregated paper	2.1E-06	*90%*	Segregated paper	8.4E-06	*90%*	Segregated paper	5.3E-05	*90%*
6	Water content, animal food waste	4.6E-07	*92%*	Water content, animal food waste	1.8E-06	*92%*	Water content, animal food waste	1.1E-05	*92%*
7	Heating value, vegetable food waste	3.7E-07	*94%*	Heating value, vegetable food waste	1.5E-06	*94%*	Heating value, vegetable food waste	9.2E-06	*94%*
8	Heating value, plastic waste	3.4E-07	*95%*	Heating value, plastic waste	1.3E-06	*95%*	Heating value, plastic waste	8.4E-06	*95%*
9	Fossil carbon content, plastic waste	2.6E-07	*96%*	Fossil carbon content, plastic waste	1E-06	*96%*	Fossil carbon content, plastic waste	6.4E-06	*96%*
10	Heating value, animal food waste	2.2E-07	*97%*	Heating value, animal food waste	8.6E-07	*97%*	Heating value, animal food waste	5.4E-06	*97%*

Table S30. Total output variance for Scenario 1 for each impact category and increasing input variance, normally distributed, assigned to the model parameters. The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are not included.

	Normal distribution analytical			**Normal distribution MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	1.65E-05	6.62E-05	4.14E-04	1.73E-05	7.05E-05	4.01E-04	*-4%*	*-6%*	*3%*
ODP	1.01E-11	4.05E-11	2.53E-10	1.05E-11	4.08E-11	2.46E-10	*-3%*	*-1%*	*3%*
HTC	2.17E-09	8.69E-09	5.43E-08	2.09E-09	8.91E-09	5.38E-08	*4%*	*-2%*	*1%*
HTNC	1.09E-07	4.37E-07	2.73E-06	1.15E-07	4.61E-07	2.72E-06	*-5%*	*-5%*	*1%*
PM	8.20E-07	3.28E-06	2.05E-05	8.48E-07	3.39E-06	1.99E-05	*-3%*	*-3%*	*3%*
IR	6.69E-08	2.68E-07	1.67E-06	6.90E-08	2.69E-07	1.62E-06	*-3%*	*-1%*	*3%*
POFP	9.31E-07	3.73E-06	2.33E-05	9.42E-07	3.58E-06	2.38E-05	*-1%*	*4%*	*-2%*
TA	2.18E-06	8.72E-06	5.45E-05	2.27E-06	8.53E-06	5.39E-05	*-4%*	*2%*	*1%*
TE	3.81E-06	1.52E-05	9.52E-05	3.83E-06	1.45E-05	9.75E-05	*-1%*	*5%*	*-2%*
FE	1.91E-09	7.63E-09	4.77E-08	2.10E-09	7.70E-09	4.68E-08	*-9%*	*-1%*	*2%*
ME	4.73E-06	1.89E-05	1.18E-04	4.77E-06	1.82E-05	1.21E-04	*-1%*	*4%*	*-2%*
ET	2.23E-05	8.91E-05	5.57E-04	2.34E-05	8.70E-05	5.61E-04	*-5%*	*2%*	*-1%*
RDFOS	3.27E-05	1.31E-04	8.18E-04	3.35E-05	1.38E-04	8.15E-04	*-2%*	*-5%*	*0%*
RD	1.31E-12	5.24E-12	3.28E-11	1.27E-12	5.14E-12	3.20E-11	*4%*	*2%*	*3%*

Table S31. Total output variance for Scenario 1 for each impact category and increasing input variance, uniformly distributed, assigned to the model parameters. The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are not included.

	Uniform distribution analytical			**Uniform distribution MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	2.21E-05	8.82E-05	5.51E-04	2.18E-05	8.52E-05	5.58E-04	*1%*	*4%*	*-1%*
ODP	1.35E-11	5.40E-11	3.37E-10	1.32E-11	5.64E-11	3.13E-10	*2%*	*-4%*	*8%*
HTC	2.90E-09	1.16E-08	7.25E-08	2.75E-09	1.17E-08	6.92E-08	*6%*	*-1%*	*5%*
HTNC	1.46E-07	5.82E-07	3.64E-06	1.35E-07	5.83E-07	3.49E-06	*8%*	*0%*	*4%*
PM	1.09E-06	4.37E-06	2.73E-05	1.07E-06	4.16E-06	2.76E-05	*2%*	*5%*	*-1%*
IR	8.92E-08	3.57E-07	2.23E-06	8.70E-08	3.72E-07	2.06E-06	*3%*	*-4%*	*8%*
POFP	1.24E-06	4.97E-06	3.10E-05	1.27E-06	4.64E-06	3.34E-05	*-2%*	*7%*	*-7%*
TA	2.91E-06	1.16E-05	7.27E-05	2.94E-06	1.10E-05	7.91E-05	*-1%*	*6%*	*-8%*
TE	5.08E-06	2.03E-05	1.27E-04	5.17E-06	1.91E-05	1.36E-04	*-2%*	*6%*	*-7%*
FE	2.54E-09	1.02E-08	6.36E-08	2.68E-09	1.05E-08	6.41E-08	*-5%*	*-3%*	*-1%*
ME	6.31E-06	2.52E-05	1.58E-04	6.45E-06	2.37E-05	1.69E-04	*-2%*	*7%*	*-7%*
ET	2.97E-05	1.19E-04	7.43E-04	2.93E-05	1.27E-04	7.17E-04	*1%*	*-6%*	*4%*
RDFOS	4.36E-05	1.74E-04	1.09E-03	4.32E-05	1.78E-04	1.08E-03	*1%*	*-2%*	*1%*
RD	1.75E-12	6.99E-12	4.37E-11	1.65E-12	7.23E-12	4.30E-11	*6%*	*-3%*	*2%*

Table S32. Total output variance for Scenario 1 for each impact category and increasing input variance, triangularly distributed (centred), assigned to the model parameters. The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are not included.

	Triangular distribution analytical			**Triangular distribution MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	1.10E-05	4.41E-05	2.76E-04	1.07E-05	4.07E-05	2.76E-04	*3%*	*8%*	*0%*
ODP	6.74E-12	2.70E-11	1.69E-10	6.63E-12	2.80E-11	1.71E-10	*2%*	*-4%*	*-1%*
HTC	1.45E-09	5.80E-09	3.62E-08	1.49E-09	5.98E-09	3.62E-08	*-3%*	*-3%*	*0%*
HTNC	7.28E-08	2.91E-07	1.82E-06	6.86E-08	3.05E-07	1.84E-06	*6%*	*-5%*	*-1%*
PM	5.46E-07	2.19E-06	1.37E-05	5.12E-07	2.33E-06	1.40E-05	*7%*	*-6%*	*-3%*
IR	4.46E-08	1.78E-07	1.12E-06	4.36E-08	1.85E-07	1.12E-06	*2%*	*-3%*	*-1%*
POFP	6.21E-07	2.48E-06	1.55E-05	6.22E-07	2.69E-06	1.60E-05	*0%*	*-8%*	*-3%*
TA	1.45E-06	5.81E-06	3.63E-05	1.43E-06	6.18E-06	3.73E-05	*2%*	*-6%*	*-3%*
TE	2.54E-06	1.02E-05	6.35E-05	2.55E-06	1.09E-05	6.50E-05	*0%*	*-7%*	*-2%*
FE	1.27E-09	5.08E-09	3.18E-08	1.31E-09	5.22E-09	3.12E-08	*-3%*	*-3%*	*2%*
ME	3.16E-06	1.26E-05	7.89E-05	3.16E-06	1.36E-05	8.10E-05	*0%*	*-7%*	*-3%*
ET	1.49E-05	5.94E-05	3.71E-04	1.46E-05	6.07E-05	3.75E-04	*2%*	*-2%*	*-1%*
RDFOS	2.18E-05	8.72E-05	5.45E-04	2.08E-05	8.90E-05	5.51E-04	*5%*	*-2%*	*-1%*
RD	8.74E-13	3.50E-12	2.19E-11	8.60E-13	3.47E-12	2.29E-11	*2%*	*1%*	*-4%*

Table S33. Total output variance for Scenario 1 for each impact category and increasing input variance, lognormally distributed, assigned to the model parameters. The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are not included.

	Lognormal distribution analytical			**Lognormal distribution MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	1.65E-05	6.62E-05	4.14E-04	1.68E-05	7.27E-05	4.02E-04	*-1%*	*-9%*	*3%*
ODP	1.01E-11	4.05E-11	2.53E-10	1.06E-11	4.03E-11	2.58E-10	*-4%*	*0%*	*-2%*
HTC	2.17E-09	8.69E-09	5.43E-08	2.13E-09	9.14E-09	5.14E-08	*2%*	*-5%*	*6%*
HTNC	1.09E-07	4.37E-07	2.73E-06	1.11E-07	4.65E-07	2.68E-06	*-1%*	*-6%*	*2%*
PM	8.20E-07	3.28E-06	2.05E-05	8.05E-07	3.43E-06	1.89E-05	*2%*	*-4%*	*8%*
IR	6.69E-08	2.68E-07	1.67E-06	6.94E-08	2.66E-07	1.70E-06	*-4%*	*1%*	*-2%*
POFP	9.31E-07	3.73E-06	2.33E-05	9.54E-07	3.93E-06	2.30E-05	*-2%*	*-5%*	*1%*
TA	2.18E-06	8.72E-06	5.45E-05	2.22E-06	9.59E-06	5.22E-05	*-2%*	*-9%*	*4%*
TE	3.81E-06	1.52E-05	9.52E-05	3.89E-06	1.60E-05	9.46E-05	*-2%*	*-5%*	*1%*
FE	1.91E-09	7.63E-09	4.77E-08	2.03E-09	7.64E-09	5.20E-08	*-6%*	*0%*	*-8%*
ME	4.73E-06	1.89E-05	1.18E-04	4.86E-06	2.00E-05	1.18E-04	*-3%*	*-5%*	*1%*
ET	2.23E-05	8.91E-05	5.57E-04	2.27E-05	9.16E-05	5.75E-04	*-2%*	*-3%*	*-3%*
RDFOS	3.27E-05	1.31E-04	8.18E-04	3.18E-05	1.32E-04	8.12E-04	*3%*	*-1%*	*1%*
RD	1.31E-12	5.24E-12	3.28E-11	1.38E-12	5.55E-12	3.48E-11	*-5%*	*-6%*	*-6%*

In-depth analysis on extremely skewed distributions

The SCs obtained for Scenario 1 are still applicable also when the parameters are associated with extremely skewed triangular distributions, *i.e.* with their mode coinciding with an extreme of the uncertainty range. The SCs are indeed related to the model structure and not the input uncertainty. Moreover, the SC calculated with average parameter values changed according to the mode of the skewed triangular distributions would not be different from the original ones for the same percent increase (10 %). The analytical output uncertainty could thus be calculated as previously explained. The analytical input uncertainty is the same whether the distribution is skewed to the left or to the right (please refer to Section SI.3).

Tables S34 and S35 show the difference between analytically calculated and sampled output uncertainties for skewed triangularly distributed parameters and for increasing uncertainty ranges. Tables S36 and S37 show results for the same distributions, but after decoupling the water parameters from the chemical composition.

The differences between the two methods are larger than those observed for the centred distributions in the previous section, being on average around 15 %, and noticeably larger for higher uncertainty ranges. This difference does not seem related to the water content parameters as it was for the previous cases, since even in Table S36 and Table S37 (obtained decoupling the water parameters) this difference sets on at least around 20 % for the highest uncertainty ranges. The skewed distribution to the left shows higher differences between analytical and sampling method with respect to the skewed distribution to the right when also water parameters were included. In general, impact categories such as ODP and IR show much lower average differences between the methods in comparison to other impact categories.

In order to better investigate the behaviour of these extremely skewed distributions, we sampled by means of a Monte Carlo analysis the contribution of each parameter to the output uncertainty for each impact category. The average difference between the analytically calculated output variance and the sampled variance for each parameter's output uncertainty is 0.3 %, with higher deviations for water content-related parameters (data not shown). Tables S38 and S39 show the results for total scenario output uncertainties for left-skewed and right-skewed distributions first including with water-related parameters, then excluding water-related parameters (Tables S40 and S41).

The analytical method approximates the results better when the sampled individual contributions to the total output uncertainty are summed rather than sampled all together, with average differences of 5 % including water-related parameters and of 1 % excluding them.

Table S34. Total output variance for Scenario 1 for each impact category and increasing input variance, triangularly distributed, assigned to the model parameters. The triangular distributions in input are completely skewed to the left (mode = min). The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are not included.

	Triangular distribution SX analytical			**Triangular distribution SX MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	2.00E-05	8.00E-05	5.00E-04	1.81E-05	7.10E-05	3.86E-04	*10%*	*13%*	*30%*
ODP	9.01E-12	3.60E-11	2.25E-10	9.28E-12	3.82E-11	2.28E-10	*-3%*	*-6%*	*-1%*
HTC	2.14E-09	8.58E-09	5.36E-08	1.94E-09	7.75E-09	4.35E-08	*10%*	*11%*	*23%*
HTNC	1.14E-07	4.57E-07	2.86E-06	9.77E-08	3.97E-07	2.15E-06	*17%*	*15%*	*33%*
PM	1.01E-06	4.03E-06	2.52E-05	8.20E-07	3.34E-06	1.89E-05	*23%*	*21%*	*33%*
IR	5.96E-08	2.38E-07	1.49E-06	6.12E-08	2.52E-07	1.50E-06	*-3%*	*-5%*	*-1%*
POFP	1.18E-06	4.70E-06	2.94E-05	1.04E-06	4.21E-06	2.49E-05	*13%*	*12%*	*18%*
TA	3.07E-06	1.23E-05	7.68E-05	2.64E-06	1.02E-05	5.72E-05	*16%*	*20%*	*34%*
TE	4.67E-06	1.87E-05	1.17E-04	4.16E-06	1.70E-05	1.01E-04	*12%*	*10%*	*16%*
FE	1.69E-09	6.78E-09	4.24E-08	1.55E-09	6.54E-09	3.10E-08	*10%*	*4%*	*36%*
ME	5.82E-06	2.33E-05	1.45E-04	5.18E-06	2.11E-05	1.26E-04	*12%*	*10%*	*16%*
ET	1.98E-05	7.92E-05	4.95E-04	1.83E-05	6.63E-05	3.44E-04	*8%*	*20%*	*44%*
RDFOS	3.72E-05	1.49E-04	9.29E-04	3.10E-05	1.24E-04	7.35E-04	*20%*	*20%*	*26%*
RD	1.19E-12	4.76E-12	2.97E-11	1.24E-12	4.69E-12	2.10E-11	*-4%*	*1%*	*42%*

Table S35. Total output variance for Scenario 1 for each impact category and increasing input variance, triangularly distributed, assigned to the model parameters. The triangular distributions in input are completely skewed to the right (mode = max). The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are not included.

	Triangular distribution DX analytical			**Triangular distribution DX MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	2.00E-05	8.00E-05	5.00E-04	1.98E-05	8.86E-05	5.77E-04	*1%*	*-10%*	*-13%*
ODP	9.01E-12	3.60E-11	2.25E-10	9.01E-12	3.76E-11	2.31E-10	*0%*	*-4%*	*-3%*
HTC	2.14E-09	8.58E-09	5.36E-08	2.07E-09	8.49E-09	5.84E-08	*3%*	*1%*	*-8%*
HTNC	1.14E-07	4.57E-07	2.86E-06	1.10E-07	4.64E-07	3.24E-06	*4%*	*-1%*	*-12%*
PM	1.01E-06	4.03E-06	2.52E-05	8.98E-07	3.99E-06	2.59E-05	*12%*	*1%*	*-3%*
IR	5.96E-08	2.38E-07	1.49E-06	5.93E-08	2.48E-07	1.52E-06	*0%*	*-4%*	*-2%*
POFP	1.18E-06	4.70E-06	2.94E-05	1.12E-06	4.81E-06	2.82E-05	*5%*	*-2%*	*4%*
TA	3.07E-06	1.23E-05	7.68E-05	2.86E-06	1.25E-05	7.36E-05	*7%*	*-2%*	*4%*
TE	4.67E-06	1.87E-05	1.17E-04	4.54E-06	1.92E-05	1.12E-04	*3%*	*-3%*	*4%*
FE	1.69E-09	6.78E-09	4.24E-08	1.79E-09	8.00E-09	6.19E-08	*-5%*	*-15%*	*-31%*
ME	5.82E-06	2.33E-05	1.45E-04	5.63E-06	2.40E-05	1.40E-04	*3%*	*-3%*	*4%*
ET	1.98E-05	7.92E-05	4.95E-04	2.15E-05	8.84E-05	6.95E-04	*-8%*	*-10%*	*-29%*
RDFOS	3.72E-05	1.49E-04	9.29E-04	3.37E-05	1.43E-04	9.86E-04	*10%*	*4%*	*-6%*
RD	1.19E-12	4.76E-12	2.97E-11	1.16E-12	4.61E-12	2.70E-11	*2%*	*3%*	*10%*

Table S36. Total output variance for Scenario 1 for each impact category and increasing input variance, triangularly distributed, assigned to the model parameters. The triangular distributions in input are completely skewed to the left (mode = min). The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are included.

	Triangular distribution SX analytical			**Triangular distribution SX MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	1.47E-05	5.88E-05	3.68E-04	1.50E-05	5.23E-05	2.85E-04	*-2%*	*12%*	*29%*
ODP	8.99E-12	3.60E-11	2.25E-10	8.56E-12	3.57E-11	2.14E-10	*5%*	*1%*	*5%*
HTC	1.93E-09	7.73E-09	4.83E-08	1.98E-09	7.50E-09	3.79E-08	*-3%*	*3%*	*27%*
HTNC	9.71E-08	3.88E-07	2.43E-06	9.57E-08	3.77E-07	1.87E-06	*1%*	*3%*	*29%*
PM	7.28E-07	2.91E-06	1.82E-05	7.01E-07	2.69E-06	1.45E-05	*4%*	*8%*	*25%*
IR	5.95E-08	2.38E-07	1.49E-06	5.64E-08	2.35E-07	1.41E-06	*6%*	*1%*	*6%*
POFP	8.28E-07	3.31E-06	2.07E-05	8.45E-07	2.85E-06	1.74E-05	*-2%*	*16%*	*19%*
TA	1.94E-06	7.75E-06	4.84E-05	1.95E-06	6.19E-06	3.79E-05	*-1%*	*25%*	*28%*
TE	3.39E-06	1.35E-05	8.46E-05	3.46E-06	1.17E-05	7.12E-05	*-2%*	*16%*	*19%*
FE	1.69E-09	6.78E-09	4.24E-08	1.62E-09	5.77E-09	2.93E-08	*4%*	*18%*	*44%*
ME	4.21E-06	1.68E-05	1.05E-04	4.30E-06	1.46E-05	8.93E-05	*-2%*	*15%*	*18%*
ET	1.98E-05	7.92E-05	4.95E-04	1.82E-05	7.26E-05	3.75E-04	*9%*	*9%*	*32%*
RDFOS	2.91E-05	1.16E-04	7.27E-04	3.04E-05	1.13E-04	5.49E-04	*-4%*	*3%*	*32%*
RD	1.17E-12	4.66E-12	2.91E-11	1.28E-12	4.84E-12	2.97E-11	*-9%*	*-4%*	*-2%*

Table S37. Total output variance for Scenario 1 for each impact category and increasing input variance, triangularly distributed, assigned to the model parameters. The triangular distributions in input are completely skewed to the right (mode = max). The output variance was calculated analytically and by means of Monte Carlo sampling (1000 sampling points); the percent variation of the analytical with respect to the sampled output variance is reported. Water content parameters are included.

	Triangular distribution DX analytical			**Triangular distribution DX MC**			***Variation analytical from MC***		
	10%	**20%**	**50%**	**10%**	**20%**	**50%**	***10%***	***20%***	***50%***
Impact category	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*	*[%]*
GWP	1.47E-05	5.88E-05	3.68E-04	1.53E-05	6.22E-05	2.90E-04	*-4%*	*-5%*	*27%*
ODP	8.99E-12	3.60E-11	2.25E-10	8.94E-12	3.73E-11	2.22E-10	*1%*	*-4%*	*1%*
HTC	1.93E-09	7.73E-09	4.83E-08	2.05E-09	8.14E-09	3.98E-08	*-6%*	*-5%*	*21%*
HTNC	9.71E-08	3.88E-07	2.43E-06	9.84E-08	4.13E-07	1.97E-06	*-1%*	*-6%*	*23%*
PM	7.28E-07	2.91E-06	1.82E-05	7.67E-07	2.94E-06	1.44E-05	*-5%*	*-1%*	*26%*
IR	5.95E-08	2.38E-07	1.49E-06	5.89E-08	2.46E-07	1.46E-06	*1%*	*-3%*	*2%*
POFP	8.28E-07	3.31E-06	2.07E-05	9.05E-07	3.54E-06	1.75E-05	*-9%*	*-7%*	*19%*
TA	1.94E-06	7.75E-06	4.84E-05	2.19E-06	8.28E-06	3.80E-05	*-12%*	*-6%*	*28%*
TE	3.39E-06	1.35E-05	8.46E-05	3.69E-06	1.45E-05	7.20E-05	*-8%*	*-7%*	*17%*
FE	1.69E-09	6.78E-09	4.24E-08	1.82E-09	7.76E-09	2.99E-08	*-7%*	*-13%*	*42%*
ME	4.21E-06	1.68E-05	1.05E-04	4.58E-06	1.70E-05	8.98E-05	*-8%*	*-1%*	*17%*
ET	1.98E-05	7.92E-05	4.95E-04	2.00E-05	8.67E-05	3.67E-04	*-1%*	*-9%*	*35%*
RDFOS	2.91E-05	1.16E-04	7.27E-04	2.97E-05	1.21E-04	5.88E-04	*-2%*	*-4%*	*24%*
RD	1.17E-12	4.66E-12	2.91E-11	1.17E-12	4.77E-12	2.95E-11	*0%*	*-2%*	*-1%*

Table S38. Comparison between total output variances for skewed triangular distributions with 50% uncertainty (mode = min). The output variance was calculated analytically, sampled with Monte Carlo (1000 sampling points) and summed by individual output variances for the parameters sampled with Monte Carlo (1000 sampling points). The variation from the analytical output variance is reported for both Monte Carlo samples. Water parameters are included.

Triangular distribution, skewed to the left, 50% uncertainty					
	Output variance			***Variation from analytical***	
	Total analytical	**Total sampled MC**	**Total sum MC**	***Total sampled MC***	***Total sum MC***
Impact category	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*
GWP	5.00E-04	3.86E-04	4.93E-04	*30%*	*2%*
ODP	2.25E-10	2.28E-10	2.35E-10	*-1%*	*-4%*
HTC	5.36E-08	4.35E-08	5.24E-08	*23%*	*2%*
HTNC	2.86E-06	2.15E-06	2.71E-06	*33%*	*5%*
PM	2.52E-05	1.89E-05	2.27E-05	*33%*	*11%*
IR	1.49E-06	1.50E-06	1.55E-06	*-1%*	*-4%*
POFP	2.94E-05	2.49E-05	2.61E-05	*18%*	*13%*
TA	7.68E-05	5.72E-05	6.65E-05	*34%*	*15%*
TE	1.17E-04	1.01E-04	1.04E-04	*16%*	*12%*
FE	4.24E-08	3.10E-08	4.28E-08	*36%*	*-1%*
ME	1.45E-04	1.26E-04	1.30E-04	*16%*	*12%*
ET	4.95E-04	3.44E-04	4.83E-04	*44%*	*2%*
RDFOS	9.29E-04	7.35E-04	8.72E-04	*26%*	*7%*
RD	2.97E-11	2.10E-11	3.09E-11	*42%*	*-4%*

Table S39. Comparison between total output variances for skewed triangular distributions with 50% uncertainty (mode = max). The output variance was calculated analytically, sampled with Monte Carlo (1000 sampling points) and summed by individual output variances for the parameters sampled with Monte Carlo (1000 sampling points). The variation from the analytical output variance is reported for both Monte Carlo samples. Water parameters are included.

Triangular distribution, skewed to the right, 50% uncertainty					
	Output variance			***Variation from analytical***	
	Total analytical	**Total sampled MC**	**Total sum MC**	***Total sampled MC***	***Total sum MC***
Impact category	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*
GWP	5.00E-04	5.77E-04	4.89E-04	*-13%*	*2%*
ODP	2.25E-10	2.31E-10	2.16E-10	*-3%*	*4%*
HTC	5.36E-08	5.84E-08	5.10E-08	*-8%*	*5%*
HTNC	2.86E-06	3.24E-06	2.69E-06	*-12%*	*6%*
PM	2.52E-05	2.59E-05	2.24E-05	*-3%*	*12%*
IR	1.49E-06	1.52E-06	1.42E-06	*-2%*	*5%*
POFP	2.94E-05	2.82E-05	2.69E-05	*4%*	*9%*
TA	7.68E-05	7.36E-05	6.76E-05	*4%*	*14%*
TE	1.17E-04	1.12E-04	1.08E-04	*4%*	*8%*
FE	4.24E-08	6.19E-08	4.25E-08	*-31%*	*0%*
ME	1.45E-04	1.40E-04	1.34E-04	*4%*	*8%*
ET	4.95E-04	6.95E-04	5.03E-04	*-29%*	*-2%*
RDFOS	9.29E-04	9.86E-04	8.49E-04	*-6%*	*9%*
RD	2.97E-11	2.70E-11	3.12E-11	*10%*	*-5%*

Table S40. Comparison between total output variances for skewed triangular distributions with 50% uncertainty (mode = min). The output variance was calculated analytically, sampled with Monte Carlo (1000 sampling points) and summed by individual output variances for the parameters sampled with Monte Carlo (1000 sampling points). The variation from the analytical output variance is reported for both Monte Carlo samples. Water parameters are not included.

Triangular distribution, skewed to the left					
	Output variance			***Variation from analytical***	
	Total analytical	**Total sampled MC**	**Total sum MC**	***Total sampled MC***	***Total sum MC***
Impact category	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*
GWP	5.00E-04	2.66E-04	3.73E-04	*38%*	*-1%*
ODP	2.25E-10	2.17E-10	2.35E-10	*4%*	*-4%*
HTC	5.36E-08	3.44E-08	4.93E-08	*41%*	*-2%*
HTNC	2.86E-06	1.70E-06	2.45E-06	*43%*	*-1%*
PM	2.52E-05	1.29E-05	1.83E-05	*41%*	*0%*
IR	1.49E-06	1.43E-06	1.55E-06	*4%*	*-4%*
POFP	2.94E-05	1.74E-05	2.03E-05	*19%*	*2%*
TA	7.68E-05	3.65E-05	4.85E-05	*33%*	*0%*
TE	1.17E-04	7.19E-05	8.27E-05	*18%*	*2%*
FE	4.24E-08	3.02E-08	4.28E-08	*40%*	*-1%*
ME	1.45E-04	8.96E-05	1.03E-04	*17%*	*2%*
ET	4.95E-04	3.36E-04	4.83E-04	*48%*	*2%*
RDFOS	9.29E-04	5.11E-04	7.43E-04	*42%*	*-2%*
RD	2.97E-11	3.03E-11	3.04E-11	*-4%*	*-4%*

Table S41. Comparison between total output variances for skewed triangular distributions with 50% uncertainty (mode = max). The output variance was calculated analytically, sampled with Monte Carlo (1000 sampling points) and summed by individual output variances for the parameters sampled with Monte Carlo (1000 sampling points). The variation from the analytical output variance is reported for both Monte Carlo samples. Water parameters are included.

Triangular distribution, skewed to the right					
	Output variance			***Variation from analytical***	
	Total analytical	**Total sampled MC**	**Total sum MC**	***Total sampled MC***	***Total sum MC***
Impact category	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*
GWP	5.00E-04	4.58E-04	3.67E-04	*-20%*	*0%*
ODP	2.25E-10	2.20E-10	2.15E-10	*2%*	*4%*
HTC	5.36E-08	6.08E-08	4.78E-08	*-21%*	*1%*
HTNC	2.86E-06	3.09E-06	2.43E-06	*-21%*	*0%*
PM	2.52E-05	2.19E-05	1.79E-05	*-17%*	*2%*
IR	1.49E-06	1.45E-06	1.42E-06	*3%*	*5%*
POFP	2.94E-05	2.52E-05	2.11E-05	*-18%*	*-2%*
TA	7.68E-05	5.89E-05	4.93E-05	*-18%*	*-2%*
TE	1.17E-04	1.10E-04	8.60E-05	*-23%*	*-2%*
FE	4.24E-08	5.52E-08	4.25E-08	*-23%*	*0%*
ME	1.45E-04	1.27E-04	1.07E-04	*-17%*	*-2%*
ET	4.95E-04	6.55E-04	5.03E-04	*-24%*	*-2%*
RDFOS	9.29E-04	9.00E-04	7.19E-04	*-19%*	*1%*
RD	2.97E-11	2.73E-11	3.07E-11	*7%*	*-5%*

In connection with what observed for the ODP and IR impact category, the results suggest that the analytical method approximates better the behaviour of the Monte Carlo when fewer or only one parameter is modelled. Then, when the number of summed parameters increases, the sampled uncertainty diverges from the analytical value.

This behaviour can be observed from the plotted probability distribution functions in Figures S27 – S34. Figures S27 – S30 show the plotted probability distribution functions obtained from the Monte Carlo sampling. The plotted distributions correspond for the total output uncertainty sampled for the impact category GWP for increasing uncertainty ranges. For Figures S27 and S28 the water parameters were included, while they were excluded for Figures S29 and S30. In all cases it can be observed that the distribution reduces its skewness for increasing uncertainty ranges. In the case of the skewed distribution to the right when water parameters are included (Figure S28) the distribution obtained for the 50 % of the uncertainty range is less offset from the distributions for 10 and 20 % uncertainty ranges than in the other cases, explaining the lower difference from the analytical result in that case.

In contrast to these distributions, in the case when impact categories are represented just by one or two parameters the probability distribution function remains skewed even for increasingly larger uncertainty ranges. An example is provided in Figures S31 – S34. The total uncertainty sampled for the impact category ODP was sampled for increasing uncertainty ranges, in the cases of both left- or right-skewed triangular distribution, with and without water parameters included. The probability distribution functions were compared to the individual one of the aluminium recovery efficiencies for all the above mentioned cases, since this parameter was found to contribute to the 99 % of the uncertainty for this impact category. As expected, the sampled distribution is very skewed, explaining why the analytical uncertainty was best fitting the sampled uncertainty in this case.

The explanation for the behaviour of the GWP impact category (and other impact categories characterized by an output uncertainty given by the sum of single parameter uncertainties with a similar order of magnitude) lies in the central limit theorem. The theorem states that, under fairly general conditions, the sum of independent random variables will be asymptotically normally distributed (Gnedenko and Kolmogorov, 1954). In particular, in the version of Lyapounov's central limit theorem, if we have small third absolute moments (skewness), the distribution of the sum will tend to a normal distribution (Billingsley, 1995). This condition is fulfilled if we have identically distributed random variables with a mean and variance. That the distribution for the cases of ODP and IR remains skewed and thus very non-normal could possibly be explained by the fact that the choice of distribution violates the convergence to 0 of the third moment expression divided by the variance expression, or that the convergence at least is very slow (due to the different order of magnitude of the summed variables).

Indeed, Tables S42 – S45 show that for the highest uncertainty ranges, the impact categories were more parameters contribute to the total uncertainty are better represented analytically by a triangular distribution centred. Likewise, this does not apply for those categories represented only by one parameter, like ODP and IR.

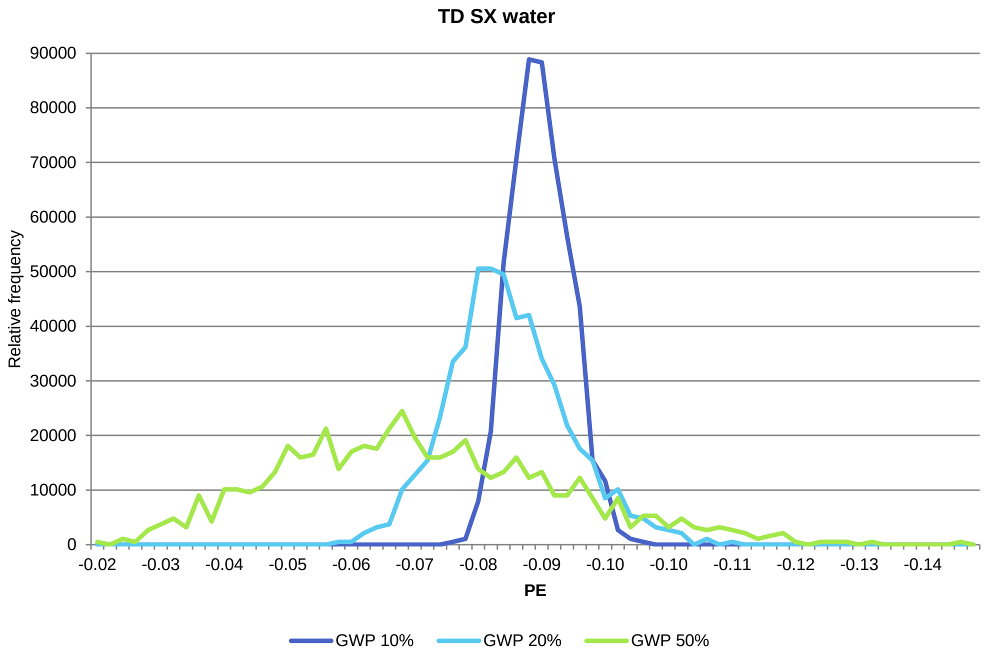


Figure S27. Probability distribution functions for the total uncertainty associated to the impact category GWP for increasing uncertainty ranges. The parameters in the model are all triangularly skewed distributions to the left (mode = min). Water parameters are included.

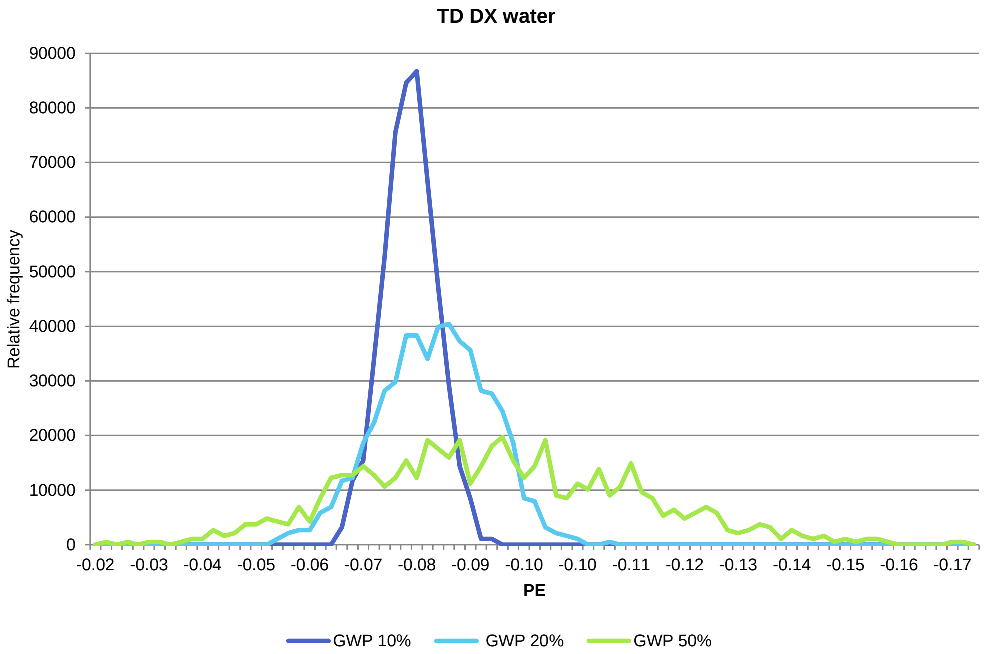


Figure S28. Probability distribution functions for the total uncertainty associated to the impact category GWP for increasing uncertainty ranges. The parameters in the model are all triangularly skewed distributions to the right (mode = max). Water parameters are included.

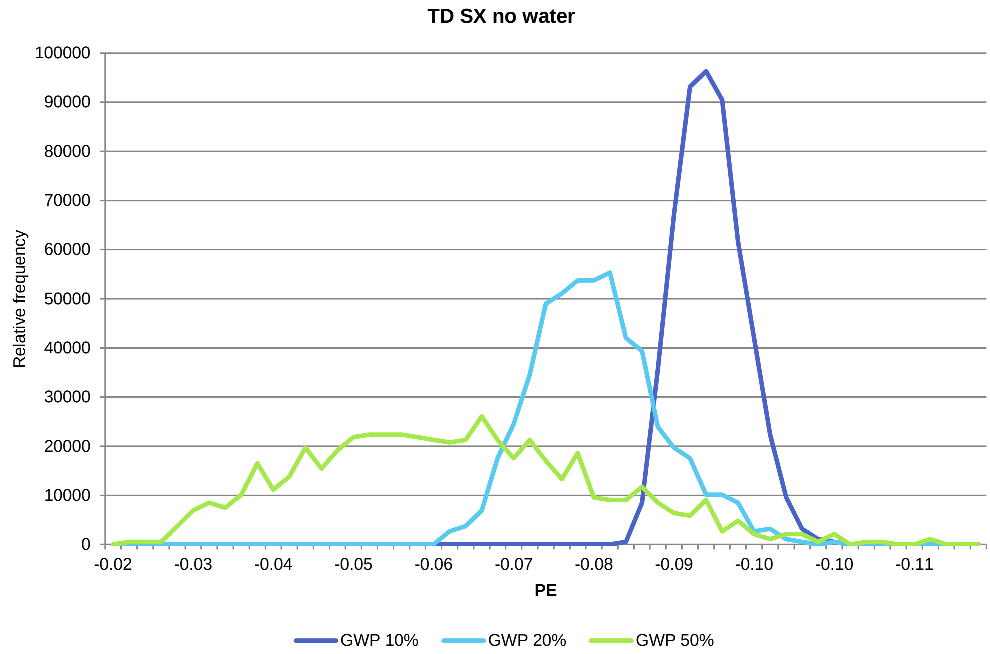


Figure S29. Probability distribution functions for the total uncertainty associated to the impact category GWP for increasing uncertainty ranges. The parameters in the model are all triangularly skewed distributions to the left (mode = min). Water parameters are not included.

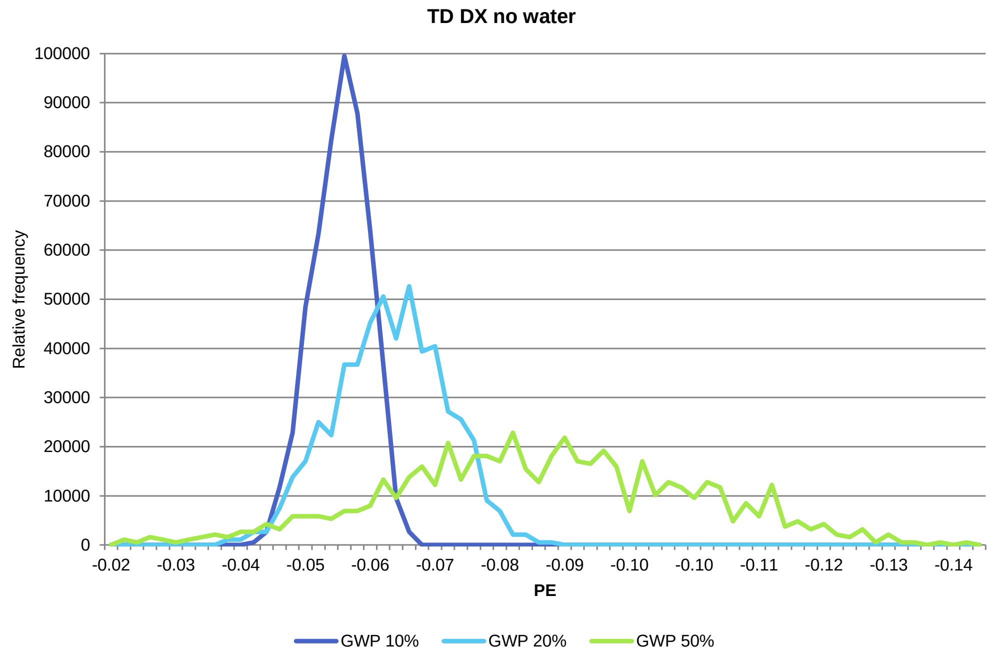


Figure S30. Probability distribution functions for the total uncertainty associated to the impact category GWP for increasing uncertainty ranges. The parameters in the model are all triangularly skewed distributions to the right (mode = max). Water parameters are not included.

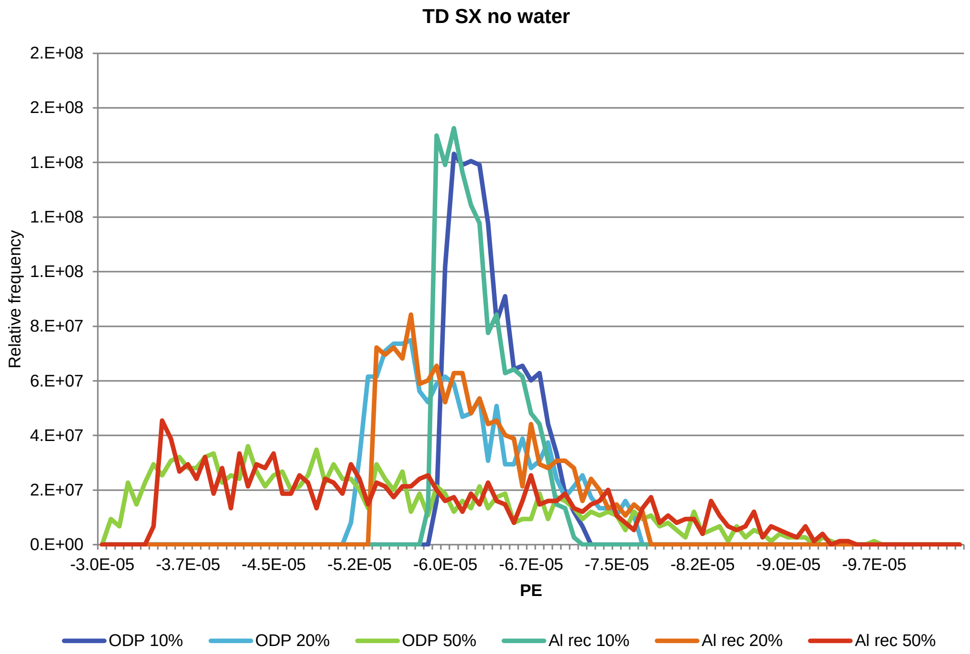


Figure S31. Probability distribution functions for the total uncertainty associated to the impact category ODP and the parameter "aluminium recovery" for increasing uncertainty ranges. The parameters in the model are all triangularly skewed distributions to the left (mode = min). Water parameters are included.

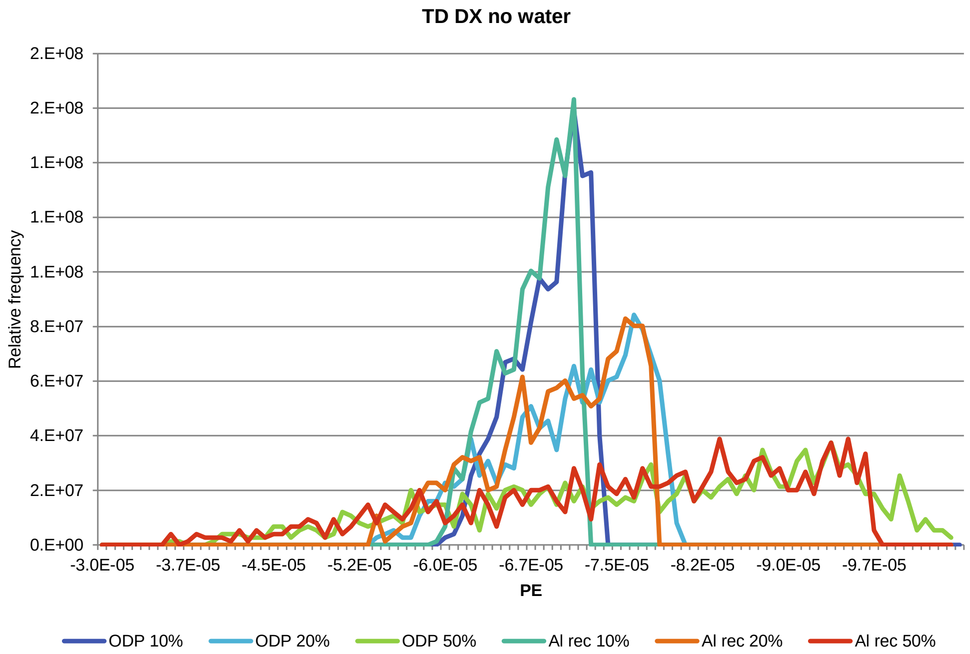


Figure S32. Probability distribution functions for the total uncertainty associated to the impact category ODP and the parameter "aluminium recovery" for increasing uncertainty ranges. The parameters in the model are all triangularly skewed distributions to the right (mode = max). Water parameters are included.

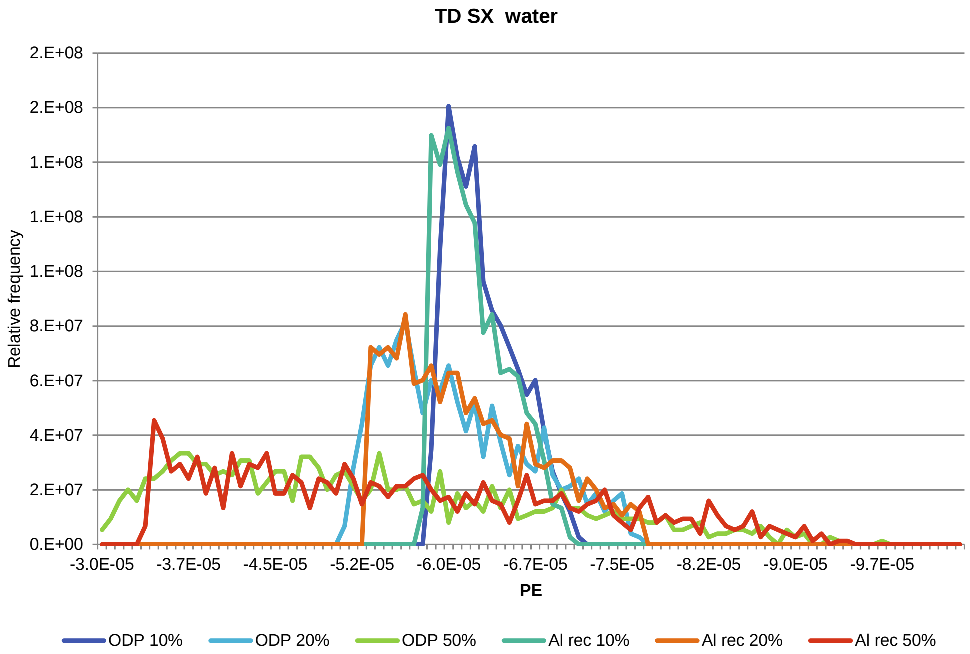


Figure S33. Probability distribution functions for the total uncertainty associated to the impact category ODP and the parameter “aluminium recovery” for increasing uncertainty ranges. The parameters in the model are all triangularly skewed distributions to the left (mode = min). Water parameters are not included.

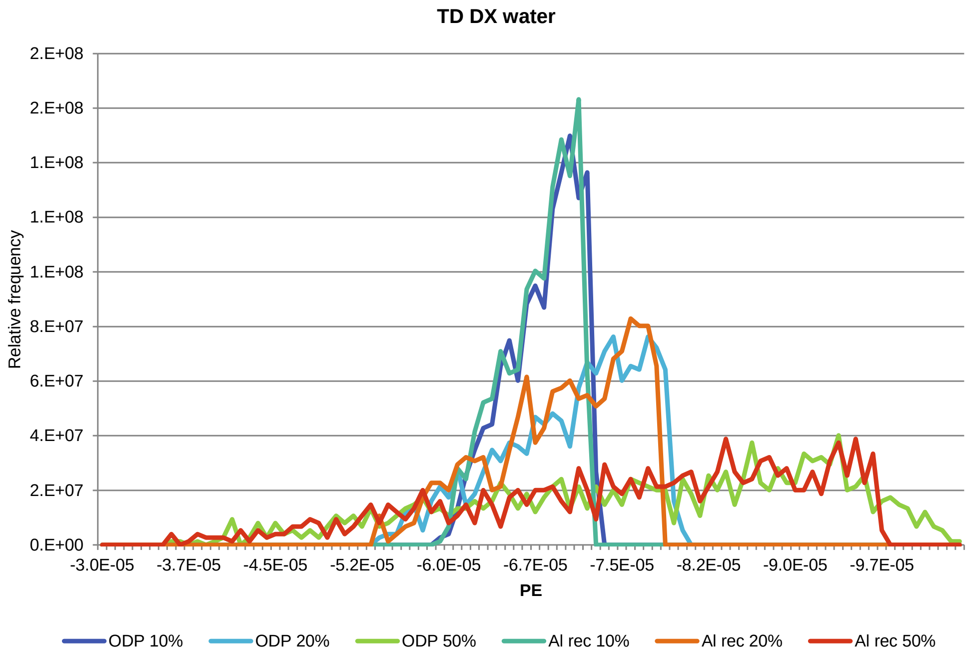


Figure S34. Probability distribution functions for the total uncertainty associated to the impact category ODP and the parameter “aluminium recovery” for increasing uncertainty ranges. The parameters in the model are all triangularly skewed distributions to the right (mode = max). Water parameters are not included.

Table S42. Comparison of the difference between analytical uncertainty calculated for triangular skewed and triangular centred from the sampled output uncertainty. The triangular distribution is skewed to the left. Water parameters are included.

Triangular distribution, skewed to the left						
	Analytical: TD Skewed SX			Analytical: TD Centred		
	Variation from MC TD Skewed SX			***Variation from MC TD Skewed SX***		
	10%	***20%***	***50%***	***10%***	***20%***	***50%***
Impact category	*[%]*	*[%]*	*[%]*	*[%]*	*[%]*	*[%]*
GWP	*10%*	*13%*	*30%*	*-17%*	*-15%*	*-3%*
ODP	*-3%*	*-6%*	*-1%*	*-27%*	*-29%*	*-26%*
HTC	*10%*	*11%*	*23%*	*-17%*	*-17%*	*-8%*
HTNC	*17%*	*15%*	*33%*	*-12%*	*-14%*	*0%*
PM	*23%*	*21%*	*33%*	*-8%*	*-10%*	*0%*
IR	*-3%*	*-5%*	*-1%*	*-27%*	*-29%*	*-25%*
POFP	*13%*	*12%*	*18%*	*-15%*	*-16%*	*-12%*
TA	*16%*	*20%*	*34%*	*-13%*	*-10%*	*1%*
TE	*12%*	*10%*	*16%*	*-16%*	*-17%*	*-13%*
FE	*10%*	*4%*	*36%*	*-18%*	*-22%*	*2%*
ME	*12%*	*10%*	*16%*	*-16%*	*-17%*	*-13%*
ET	*8%*	*20%*	*44%*	*-19%*	*-10%*	*8%*
RDFOS	*20%*	*20%*	*26%*	*-10%*	*-10%*	*-5%*
RD	*-4%*	*1%*	*42%*	*-28%*	*-24%*	*6%*

Table S43. Comparison of the difference between analytical uncertainty calculated for triangular skewed and triangular centred from the sampled output uncertainty. The triangular distribution is skewed to the right. Water parameters are included.

Triangular distribution, skewed to the right						
	Analytical: TD Skewed DX			Analytical: TD Centred		
	Variation from MC TD Skewed DX			***Variation from MC TD Skewed DX***		
	10%	***20%***	***50%***	***10%***	***20%***	***50%***
Impact category	*[%]*	*[%]*	*[%]*	*[%]*	*[%]*	*[%]*
GWP	*1%*	*-10%*	*-13%*	*-24%*	*-32%*	*-35%*
ODP	*0%*	*-4%*	*-3%*	*-25%*	*-28%*	*-27%*
HTC	*3%*	*1%*	*-8%*	*-22%*	*-24%*	*-31%*
HTNC	*4%*	*-1%*	*-12%*	*-22%*	*-26%*	*-34%*
PM	*12%*	*1%*	*-3%*	*-16%*	*-24%*	*-27%*
IR	*0%*	*-4%*	*-2%*	*-25%*	*-28%*	*-27%*
POFP	*5%*	*-2%*	*4%*	*-22%*	*-27%*	*-22%*
TA	*7%*	*-2%*	*4%*	*-19%*	*-26%*	*-22%*
TE	*3%*	*-3%*	*4%*	*-23%*	*-27%*	*-22%*
FE	*-5%*	*-15%*	*-31%*	*-29%*	*-36%*	*-49%*
ME	*3%*	*-3%*	*4%*	*-22%*	*-27%*	*-22%*
ET	*-8%*	*-10%*	*-29%*	*-31%*	*-33%*	*-47%*
RDFOS	*10%*	*4%*	*-6%*	*-17%*	*-22%*	*-29%*
RD	*2%*	*3%*	*10%*	*-23%*	*-23%*	*-17%*

Table S44. Comparison of the difference between analytical uncertainty calculated for triangular skewed and triangular centred from the sampled output uncertainty. The triangular distribution is skewed to the left. Water parameters are not included.

Triangular distribution, skewed to the left						
	Analytical: TD Skewed SX			Analytical: TD Centred		
	Variation from MC TD Skewed SX			***Variation from MC TD Skewed SX***		
	10%	***20%***	***50%***	***10%***	***20%***	***50%***
Impact category	*[%]*	*[%]*	*[%]*	*[%]*	*[%]*	*[%]*
GWP	*-2%*	*12%*	*29%*	*-27%*	*-16%*	*-3%*
ODP	*5%*	*1%*	*5%*	*-21%*	*-24%*	*-21%*
HTC	*-3%*	*3%*	*27%*	*-27%*	*-23%*	*-5%*
HTNC	*1%*	*3%*	*29%*	*-24%*	*-23%*	*-3%*
PM	*4%*	*8%*	*25%*	*-22%*	*-19%*	*-6%*
IR	*6%*	*1%*	*6%*	*-21%*	*-24%*	*-21%*
POFP	*-2%*	*16%*	*19%*	*-26%*	*-13%*	*-11%*
TA	*-1%*	*25%*	*28%*	*-26%*	*-6%*	*-4%*
TE	*-2%*	*16%*	*19%*	*-27%*	*-13%*	*-11%*
FE	*4%*	*18%*	*44%*	*-22%*	*-12%*	*8%*
ME	*-2%*	*15%*	*18%*	*-27%*	*-13%*	*-12%*
ET	*9%*	*9%*	*32%*	*-18%*	*-18%*	*-1%*
RDFOS	*-4%*	*3%*	*32%*	*-28%*	*-23%*	*-1%*
RD	*-9%*	*-4%*	*-2%*	*-32%*	*-28%*	*-27%*

Table S45. Comparison of the difference between analytical uncertainty calculated for triangular skewed and triangular centred from the sampled output uncertainty. The triangular distribution is skewed to the right. Water parameters are not included.

Triangular distribution, skewed to the right						
	Analytical: TD Skewed DX			Analytical: TD Centred		
	Variation from MC TD Skewed DX			***Variation from MC TD Skewed DX***		
	10%	***20%***	***50%***	***10%***	***20%***	***50%***
Impact category	*[%]*	*[%]*	*[%]*	*[%]*	*[%]*	*[%]*
GWP	*-4%*	*-5%*	*27%*	*-28%*	*-29%*	*-5%*
ODP	*1%*	*-4%*	*1%*	*-25%*	*-28%*	*-24%*
HTC	*-6%*	*-5%*	*21%*	*-29%*	*-29%*	*-9%*
HTNC	*-1%*	*-6%*	*23%*	*-26%*	*-29%*	*-8%*
PM	*-5%*	*-1%*	*26%*	*-29%*	*-26%*	*-5%*
IR	*1%*	*-3%*	*2%*	*-24%*	*-27%*	*-24%*
POFP	*-9%*	*-7%*	*19%*	*-31%*	*-30%*	*-11%*
TA	*-12%*	*-6%*	*28%*	*-34%*	*-30%*	*-4%*
TE	*-8%*	*-7%*	*17%*	*-31%*	*-30%*	*-12%*
FE	*-7%*	*-13%*	*42%*	*-30%*	*-34%*	*6%*
ME	*-8%*	*-1%*	*17%*	*-31%*	*-26%*	*-12%*
ET	*-1%*	*-9%*	*35%*	*-26%*	*-31%*	*1%*
RDFOS	*-2%*	*-4%*	*24%*	*-26%*	*-28%*	*-7%*
RD	*0%*	*-2%*	*-1%*	*-25%*	*-27%*	*-26%*

The information regarding how many parameters are required to well represent the total output uncertainty for an impact category can be already achieved by the hierarchy obtained by the much simpler case illustrated in the article. In particular, we refer to Table 3 and Figure 3 in the article. Moreover, from the sampled individual parameter uncertainties employed to calculate the additive uncertainty for Tables S38 – S41, we could observe that the hierarchy between individual parameters' contributions to the total output uncertainty was unchanged with respect to the one calculated analytically. In fact, as in the other cases presented previously, this hierarchy is unchanged when all parameters are characterized by the same uncertainty.

We have tested whether this hierarchy could still be a valid indication of a limited number of parameters with which the results of the discernibility analysis could be approximated, reducing the computational times.

Methods

The parameters already illustrated in the article were expressed as extremely skewed triangular distributions, both to the left and to the right) for Scenario 1 and for Scenario 2, with 50 % uncertainty. The total output uncertainty was sampled with the fewer parameters identified by the hierarchy and for the full parameter set. The sampling was carried out by means of a Monte Carlo analysis with 1000 sampling points. Further uncertainties were sampled for 100000 sampling points for both cases without including water parameters.

Results and discussion

Results for the discernibility analysis between Scenario 1 and Scenario 2 are shown in Tables S46 (left-skewed) and S47 (right-skewed). Scores for HTC, HTNC and ET were omitted since the results were not overlapping, thus not needing a discernibility analysis (as already discussed in the article).

The results obtained as "percentage of scores where Scenario 1 is preferable over Scenario 2" show a much higher variation than the one presented in the article for 10 % uncertainty range. In general, the results have shifted for all impact categories towards 50 %, indicating that the width of the uncertainty range is causing an overlap between the distributions of the results of the two scenarios. Moreover, the results obtained for the full sets of parameters with 1000 sampling points are considerably different than the ones obtained for the same sets with 100000 sampling points (especially for the left-skewed distribution case), suggesting that the amplitude of the output uncertainty requires a higher number of Monte Carlo runs in order to be well represented.

Table S46. Discernibility analysis between Scenario 1 and Scenario 2 modelled with triangular distributions extremely skewed to the left (min = mode) and 50% uncertainty range.

		GWP	**ODP**	**PM**	**IR**	**POFP**	**TA**	**TE**	**RDFOS**	**RD**
With water	**i=6**; $N=10^3$	78%	61%	87%	55%	68%	94%	68%	77%	50%
	i=80; $N=10^3$	65%	48%	54%	48%	51%	57%	51%	74%	60%
Without water	**i=6**; $N=10^3$	69%	61%	61%	55%	48%	65%	49%	74%	50%
	i=6; $N=10^5$	73%	46%	60%	46%	47%	45%	39%	67%	59%
	i=70; $N=10^3$	39%	47%	30%	47%	23%	27%	26%	55%	51%
	i=70; $N=10^5$	67%	49%	56%	49%	47%	55%	55%	77%	60%

Table S47. Discernibility analysis between Scenario 1 and Scenario 2 modelled with triangular distributions extremely skewed to the left (min = mode) and 50% uncertainty range.

		GWP	ODP	PM	IR	POFP	TA	TE	RDFOS	RD
With water	**i=6**; $N=10^3$	52%	47%	46%	43%	30%	37%	31%	60%	65%
	i=80; $N=10^3$	48%	47%	39%	47%	33%	41%	33%	51%	61%
Without water	**i=6**; $N=10^3$	65%	61%	52%	43%	44%	54%	46%	62%	65%
	i=6; $N=10^5$	66%	47%	53%	49%	36%	55%	36%	67%	83%
	i=70; $N=10^3$	51%	47%	41%	47%	36%	47%	37%	52%	64%
	i=70; $N=10^5$	55%	47%	44%	48%	37%	47%	38%	53%	65%

Final remarks

For extremely skewed distributions, the analytical uncertainty propagation provides a good approximation of the single parameters contributions, but not of the total output uncertainty when input uncertainties are very large. This is mostly due to a change in shape in the total output distribution of uncertainty: when a large number of variables is summed through the uncertainty propagation process, the resulting distribution tends to loose the skewness associated to the individual distributions (Gnedenko and Kolmogorov, 1954). In order for this to happen, the uncertainties of the variables have to be of the same order of magnitude, since when they differed majorly (e.g. ODP case) this change in shape was not observed.

The analytical method could still provide a useful indication of the parameters contributing mostly to the output uncertainty. The same subset selected in the main article can be used to perform a discernibility analysis. However, due to the amplitude of the uncertainty ranges, a larger number of Monte Carlo runs than the minimum 1000 is required.

The precision of the discernibility analysis is anyway lower than the one observed for lower uncertainty ranges, especially when all the parameters are considered for the analysis, due to the amplitude of the sample.

Finally, it is necessary to mention that in this case the practitioner would need to calculate the average values on which to base the Coefficient of Variation (CV) switching the parameters' values to the correspondent value of the mode of the uncertainty distribution, and to pay special attention in selecting an analytically calculated uncertainty for a triangular centred distribution when more than one parameter is required to represent the uncertainty in an impact category.

We would like to stress that these examined extremely skewed cases were fictitious and willing to explore the limits of the case study. We think that this specific case would unlikely happen in reality, since such a skewed distribution would represent poor datasets, represented only by two points and with a preferred value between the two. If this would happen for all the parameters and for such a high uncertainty range, the practitioner would rather reconsider the inventory rather than carrying out the assessment. In the next sub-section, we have presented a case with mixed distribution types and uncertainties that could more easily happen in "real life situations".

B) <u>Parameters have different uncertainty ranges and distribution types</u>

Methods

In order to test a case that would be more similar to a “real life” LCA study, we applied some arbitrary uncertainties larger than 10 % and with different uncertainty distributions to the parameters utilized for Scenario 1 and Scenario 2.

The selection of the distributions and the uncertainties were based on a hypothetical case where uncertainty given as ranges would correspond to a uniform distribution (characterized by a minimum and a maximum value), and to a triangular skewed distributions if uncertainty was given as ranges with a preferred value (please refer to section SI.3 for details about determining input uncertainties). An example of such uncertainties for Scenario 1 is provided in Table S48. Although the uncertainty ranges chosen were fictitious, we have tried to use uniform uncertainty ranges and triangular distributions as we observe in “real life” cases, i.e. uniform distributions with on average 20 % uncertainty for technology parameters and skewed triangular distributions for the input specific (waste) characteristics. In fact, the latter are usually obtained from sampling campaigns or from literature reviews, and are often described by a minimum, a maximum and a preferred or median value. For this example, we have chosen uncertainty ranges for the waste composition ranging up to the 93 % of the original value.

The SC for the parameters is unchanged with respect to the one calculated in the article, as explained in the previous sections. The analytical uncertainty for each parameter and for each impact category for both scenarios could thus be calculated according to Eq. (11) and Eq. (12). The uncertainty for each parameter for the two scenarios and for the total output uncertainty was sampled my means of a Monte Carlo analysis with 1000 sampling points.

The difference between the analytically calculated uncertainty and the sampled uncertainty was calculated for individual parameters and for the total scenarios, both including and excluding water related parameters. Moreover, the hierarchies for each impact category obtained with the different uncertainty methods were compared. Finally, we carried out a discernibility analysis between the two scenarios with a small set of parameters identified according to the hierarchical contributions of the parameters to the total uncertainty and compared the results with the ones obtained with the full parameters set.

Table S48. Mixed uncertainty distribution types and ranges used for Scenario 1. Please refer to Table S12 for the description and units associated to the parameters' IDs.

Parameter	Value	Minimum (as % of value)	Maximum (as % of value)	Distribution type
alu_rec	9.4E-01	40%	5%	Triangular skewed left
co2_pap	9.4E-02	50%	50%	Uniform
coll_glass	4.9E+00	20%	20%	Uniform
coll_pap	4.9E+00	20%	20%	Uniform
coll_res	3.3E+00	20%	20%	Uniform
cop_inc	2.5E-07	50%	50%	Uniform
elec_rec	2.2E-01	10%	10%	Uniform
glass_rec	8.9E-01	40%	5%	Triangular skewed left
glass_seg	7.2E+01	20%	20%	Uniform
gravel_rec	5.0E-01	20%	20%	Uniform
heat_rec	7.3E-01	15%	15%	Uniform
lime_rec	3.5E-02	20%	20%	Uniform
marg_iron	6.0E-01	10%	10%	Uniform
marg_pap	4.0E-01	10%	10%	Uniform
nox_inc	8.5E-04	50%	50%	Uniform
nox_pap	7.3E-04	50%	50%	Uniform
paper_rec	8.4E-01	40%	10%	Triangular skewed left
paper_seg	5.8E+01	20%	20%	Uniform
sox_inc	2.9E-06	50%	50%	Uniform
steel_rec	8.7E-01	20%	20%	Uniform
tr_glass_d	2.0E+02	30%	30%	Uniform
tr_pap_d	3.0E+01	30%	30%	Uniform
tr_pap_d2	3.7E+02	30%	30%	Uniform
tr_pap_f	1.3E-04	30%	30%	Uniform
tr_rec_f	2.0E-05	30%	30%	Uniform
tr_res_d	3.0E+01	30%	30%	Uniform
tr_res_f	9.0E-05	30%	30%	Uniform
zinc_iron	3.0E-06	50%	50%	Uniform
veg_wat	7.7E-01	20%	20%	Uniform
ani_wat	5.7E-01	20%	20%	Uniform
new_wat	1.3E-01	20%	20%	Uniform
adv_wat	8.8E-02	20%	20%	Uniform
dia_wat	4.6E-01	20%	20%	Uniform
oth_wat	7.4E-02	20%	20%	Uniform
pap_wat	2.2E-01	20%	20%	Uniform
yar_wat	4.8E-01	20%	20%	Uniform
pla_wat	1.0E-01	20%	20%	Uniform
dir_wat	2.4E-01	20%	20%	Uniform
veg_ene	1.8E+01	43%	79%	Triangular skewed right
ani_ene	2.5E+01	43%	79%	Triangular skewed right
new_ene	1.7E+01	50%	71%	Triangular skewed right
adv_ene	1.3E+01	50%	71%	Triangular skewed right
dia_ene	2.2E+01	56%	78%	Triangular skewed right
oth_ene	1.3E+01	69%	93%	Triangular skewed right
pap_ene	1.5E+01	50%	71%	Triangular skewed right
yar_ene	1.3E+01	51%	52%	Triangular skewed right
pla_ene	3.7E+01	64%	49%	Triangular skewed left
dir_ene	1.8E+01	50%	71%	Triangular skewed right
veg_fos	2.4E-03	91%	52%	Triangular skewed left
ani_fos	1.1E-02	91%	52%	Triangular skewed left
new_fos	2.2E-03	25%	32%	Triangular skewed right
adv_fos	1.7E-03	25%	32%	Triangular skewed right
dia_fos	5.5E-02	60%	60%	Triangular centred
oth_fos	1.9E-03	64%	73%	Triangular skewed right

Table S48. *(continued)* Mixed uncertainty distribution types and ranges used for Scenario 1. Please refer to Table S12 for the description and units associated to the parameters' IDs.

Parameter	Value	Minimum (as % of value)	Maximum (as % of value)	Distribution type
pap_fos	2.1E-03	25%	32%	Triangular skewed right
yar_fos	8.6E-03	62%	20%	Triangular skewed left
pla_fos	7.7E-01	54%	26%	Triangular skewed left
dir_fos	9.1E-03	25%	32%	Triangular skewed right
veg_bio	4.8E-01	91%	52%	Triangular skewed left
ani_bio	5.5E-01	91%	52%	Triangular skewed left
new_bio	4.5E-01	25%	32%	Triangular skewed right
adv_bio	3.4E-01	25%	32%	Triangular skewed right
dia_bio	5.0E-01	60%	60%	Triangular centred
oth_bio	3.8E-01	64%	73%	Triangular skewed right
pap_bio	4.1E-01	25%	32%	Triangular skewed right
yar_bio	4.2E-01	62%	20%	Triangular skewed left
pla_bio	3.9E-03	54%	26%	Triangular skewed left
dir_bio	4.5E-01	25%	32%	Triangular skewed right

Results and discussion

The analytically calculated variance fits better the sampled individual values for the output uncertainty rather than sampled full scenarios, as can be seen from Table S49 and S50. The percent difference between the methods is mostly due to the water parameters, where the analytical method shows the highest deviation with respect to the sampled values (Table S49). Table S50 shows that the difference between analytical and sampled uncertainty lowers after excluding the water content parameters.

The hierarchies obtained analytically and by means of Monte Carlo sampling are mostly identical (Table S51 and S52), as the low difference between the two methods for individual values was suggesting. We provide here an example for the impact category GWP and Scenario 1.

Overall, the impact categories behave as observed for the cases illustrated in the article, with a few parameters representing most of the uncertainty for the scenarios. Figure S35 and S36 show the behaviour of the output uncertainties with an increased number of parameters for Scenario 1, with and without the water parameters. In this mixed case, 10 parameters are a good compromise between a low number of parameters and 90 % of the uncertainty represented. If these 10 parameters are grouped, we count 17 parameters out of 80 across 14 impact categories including the water, and 15 parameters excluding it. This result is not distant from the 10 parameters identified in the cases illustrated in the article. It is necessary to remark that, obviously, for this case the ranking of the parameters is different because the uncertainty ranges considered are different. This is why a global approach to parameters' importance should strictly be considered case specific. Figure S37 shows an example of the GWP impact category, illustrating the precision of the analytical approximation, plotted together with the Monte Carlo.

After selecting 15 parameters for Scenario 1 and Scenario 2, we performed a discernibility analysis and reported the percentage of cases where Scenario 1 resulted favourable over Scenario 2. Results are reported in Table S53. The variation of the results with respect to the ones obtained for the full parameter set is around 1 – 2%. This shows that the method presented offers a valid approximation to evaluate the global importance of parameters even when uncertainties are mixed for range and distribution.

Table S49. Comparison between total output variances for Scenario 1. Parameters are associated with mixed uncertainty distributions and ranges. The output variance was calculated analytically, sampled with Monte Carlo (1000 sampling points) and summed by individual output variances for the parameters sampled with Monte Carlo (1000 sampling points). The variation from the analytical output variance is reported for both Monte Carlo samples. Water parameters are included.

Mixed distributions and uncertainty ranges, with water parameters					
	Output variance			***Variation from analytical***	
	Total analytical	**Total sampled MC**	**Total sum MC**	***Total sampled MC***	***Total sum MC***
Impact category	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*
GWP	1.10E-04	9.10E-05	1.03E-04	*21%*	*7%*
ODP	4.12E-11	4.10E-11	4.31E-11	*0%*	*-4%*
HTC	9.43E-09	7.40E-09	8.88E-09	*27%*	*6%*
HTNC	5.62E-07	4.19E-07	5.18E-07	*34%*	*8%*
PM	6.71E-06	5.04E-06	5.86E-06	*33%*	*14%*
IR	2.72E-07	2.70E-07	2.84E-07	*1%*	*-4%*
POFP	1.81E-05	1.50E-05	1.71E-05	*21%*	*6%*
TA	2.59E-05	2.05E-05	2.27E-05	*26%*	*14%*
TE	7.68E-05	6.40E-05	7.31E-05	*20%*	*5%*
FE	8.95E-09	7.83E-09	9.03E-09	*14%*	*-1%*
ME	9.60E-05	7.21E-05	9.14E-05	*33%*	*5%*
ET	1.32E-04	1.04E-04	1.32E-04	*27%*	*0%*
RDFOS	1.76E-04	1.34E-04	1.54E-04	*31%*	*14%*
RD	7.14E-12	6.96E-12	6.73E-12	*2%*	*6%*

Table S50. Comparison between total output variances for Scenario 1. Parameters are associated with mixed uncertainty distributions and ranges. The output variance was calculated analytically, sampled with Monte Carlo (1000 sampling points) and summed by individual output variances for the parameters sampled with Monte Carlo (1000 sampling points). The variation from the analytical output variance is reported for both Monte Carlo samples. Water parameters are not included.

Mixed distributions and uncertainty ranges, without water parameters					
	Output variance			***Variation from analytical***	
	Total analytical	**Total sampled MC**	**Total sum MC**	***Total sampled MC***	***Total sum MC***
Impact category	[PE^2]	[PE^2]	[PE^2]	*[%]*	*[%]*
GWP	7.79E-05	8.13E-05	7.80E-05	*-4%*	*0%*
ODP	4.11E-11	4.34E-11	4.30E-11	*-5%*	*-4%*
HTC	8.16E-09	8.56E-09	8.24E-09	*-5%*	*-1%*
HTNC	4.58E-07	4.67E-07	4.64E-07	*-2%*	*-1%*
PM	5.05E-06	5.04E-06	4.96E-06	*0%*	*2%*
IR	2.72E-07	2.86E-07	2.83E-07	*-5%*	*-4%*
POFP	1.60E-05	1.63E-05	1.59E-05	*-2%*	*0%*
TA	1.91E-05	2.06E-05	1.91E-05	*-7%*	*0%*
TE	6.91E-05	7.02E-05	6.87E-05	*-2%*	*1%*
FE	8.95E-09	7.86E-09	9.03E-09	*14%*	*-1%*
ME	8.64E-05	8.78E-05	8.60E-05	*-2%*	*0%*
ET	1.32E-04	1.25E-04	1.32E-04	*6%*	*0%*
RDFOS	1.28E-04	1.27E-04	1.28E-04	*1%*	*0%*
RD	6.99E-12	7.05E-12	6.64E-12	*-1%*	*5%*

Table S51. Parameters ranked according to their contribution to the output variance for Scenario 1, mixed uncertainties case. The output variance and its percentage of the total scenario variance are obtained summing progressively the individual variances of the corresponding parameters. Water parameters are included.

Analytical			Monte Carlo		
Parameter	Output variance [PE^2]	Represented of total [%]	Parameter	Output variance [PE^2]	Represented of total [%]
veg_wat	2.88E-05	26%	veg_wat	2.22E-05	22%
paper_rec	1.57E-05	41%	paper_rec	1.61E-05	37%
paper_seg	1.12E-05	51%	paper_seg	1.11E-05	48%
elec_rec	9.47E-06	59%	elec_rec	9.80E-06	58%
veg_ene	9.44E-06	68%	veg_ene	9.47E-06	67%
pla_ene	7.30E-06	75%	pla_ene	7.27E-06	74%
heat_rec	6.75E-06	81%	heat_rec	6.88E-06	81%
ani_ene	5.57E-06	86%	ani_ene	5.29E-06	86%
pla_fos	2.88E-06	89%	pla_fos	2.73E-06	89%
dia_ene	2.74E-06	91%	dia_ene	2.66E-06	91%
ani_wat	2.45E-06	93%	ani_wat	1.87E-06	93%
pap_ene	1.73E-06	95%	pap_ene	1.77E-06	95%
new_ene	1.48E-06	96%	new_ene	1.38E-06	96%
dir_ene	8.89E-07	97%	dir_ene	8.98E-07	97%
adv_ene	8.89E-07	98%	adv_ene	8.27E-07	98%

Table S52. Parameters ranked according to their contribution to the output variance for Scenario 1, mixed uncertainties case. The output variance and its percentage of the total scenario variance are obtained summing progressively the individual variances of the corresponding parameters. Water parameters are not included.

Analytical			Monte Carlo		
Parameter	Output variance [PE^2]	Represented of total [%]	Parameter	Output variance [PE^2]	Represented of total [%]
paper_rec	1.57E-05	20%	paper_rec	1.61E-05	21%
paper_seg	1.12E-05	35%	paper_seg	1.11E-05	35%
elec_rec	9.47E-06	47%	elec_rec	9.80E-06	47%
veg_ene	9.44E-06	59%	veg_ene	9.47E-06	60%
pla_ene	7.30E-06	68%	pla_ene	7.27E-06	69%
heat_rec	6.75E-06	77%	heat_rec	6.88E-06	78%
ani_ene	5.57E-06	84%	ani_ene	5.29E-06	84%
pla_fos	2.88E-06	88%	pla_fos	2.73E-06	88%
dia_ene	2.74E-06	91%	dia_ene	2.66E-06	91%
pap_ene	1.73E-06	93%	pap_ene	1.77E-06	94%
new_ene	1.48E-06	95%	new_ene	1.38E-06	95%
dir_ene	8.89E-07	97%	dir_ene	8.98E-07	97%
adv_ene	8.89E-07	98%	adv_ene	8.27E-07	98%
oth_ene	6.88E-07	99%	oth_ene	6.77E-07	98%
yar_ene	2.75E-07	99%	yar_ene	2.96E-07	99%

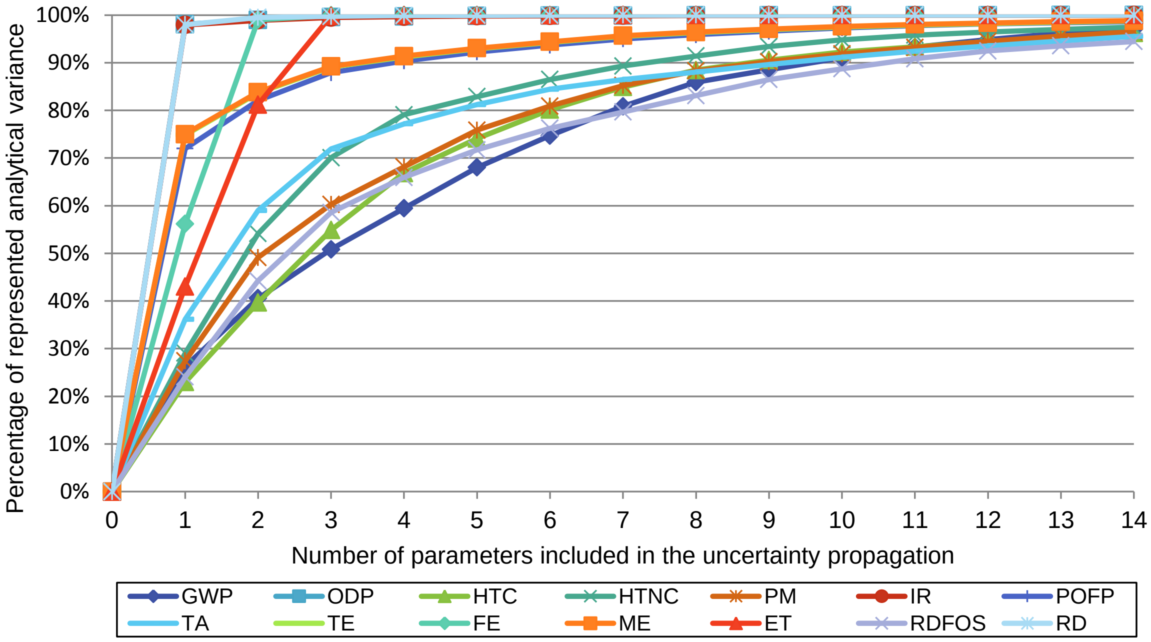


Figure S35. Percentage of the total analytical variance reached with a variable number of parameters included in the propagation for Scenario 1, mixed uncertainty case. Water parameters are included. The lines represent the impact categories.

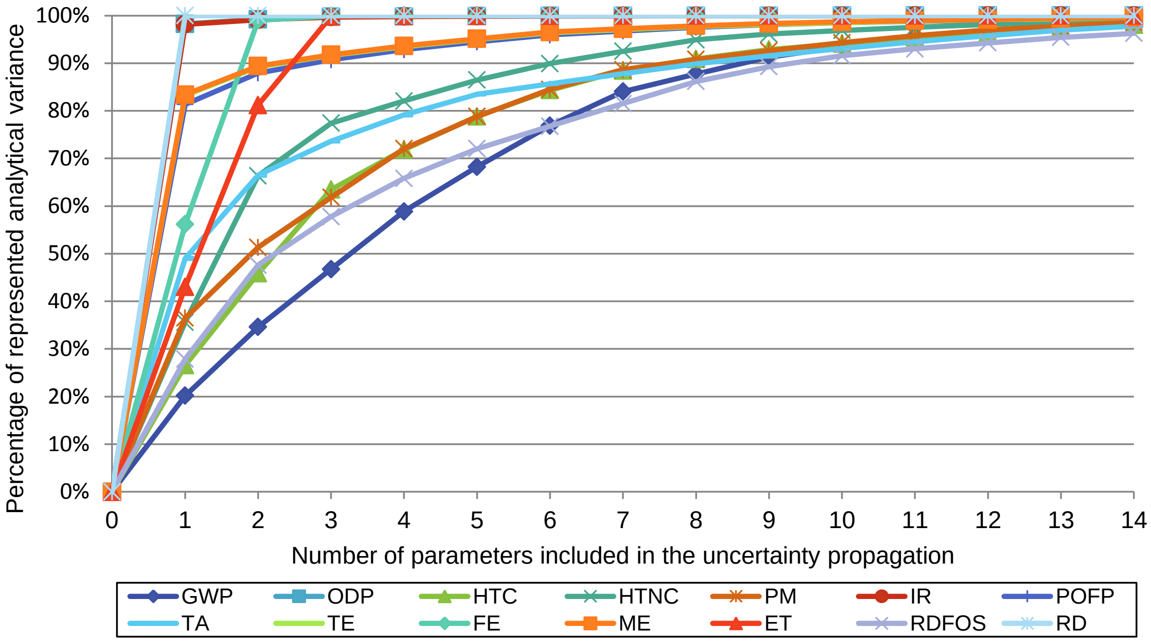


Figure S36. Percentage of the total analytical variance reached with a variable number of parameters included in the propagation for Scenario 1, mixed uncertainty case. Water parameters are included. The lines represent the impact categories.

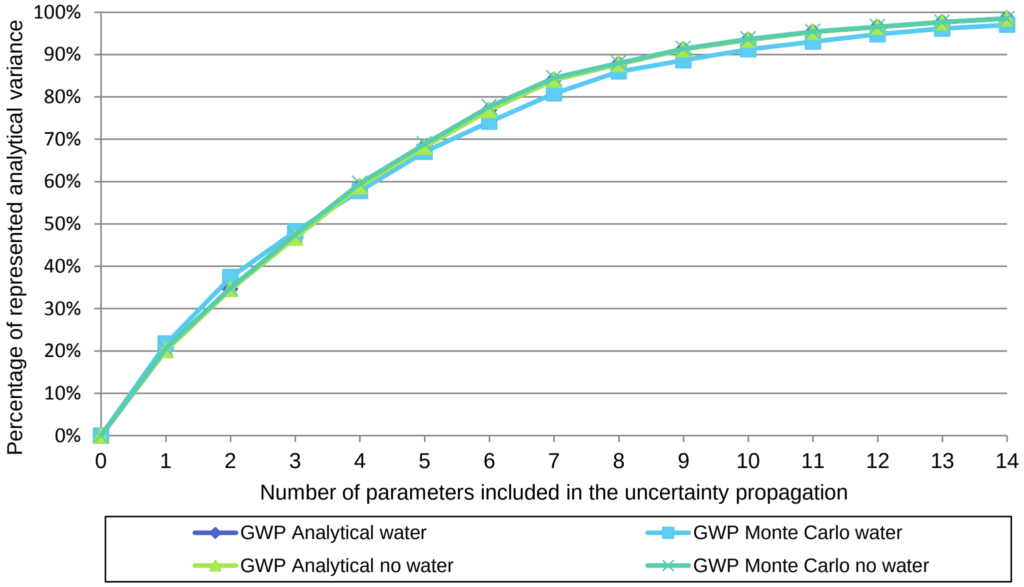


Figure S37. Percentage of the total analytical variance reached with a variable number of parameters included in the propagation for Scenario 1, mixed uncertainty case, for the impact category GWP. The lines represent the different uncertainty propagation methods: analytical and Monte Carlo.

Table S53. Discernibility analysis between Scenario 1 and Scenario 2, mixed uncertainty case. Water parameters are excluded.

	GWP	ODP	HTC	HTNC	PM	IR	POFP	TA	TE	FE	ME	ET	RDFOS	RD
i=15	85%	45%	100%	39%	63%	45%	46%	61%	46%	100%	85%	100%	88%	70%
i=70	82%	45%	100%	40%	58%	45%	44%	59%	45%	100%	95%	100%	89%	72%

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